



AI in Space: From Earth Orbit to Mars and Beyond!

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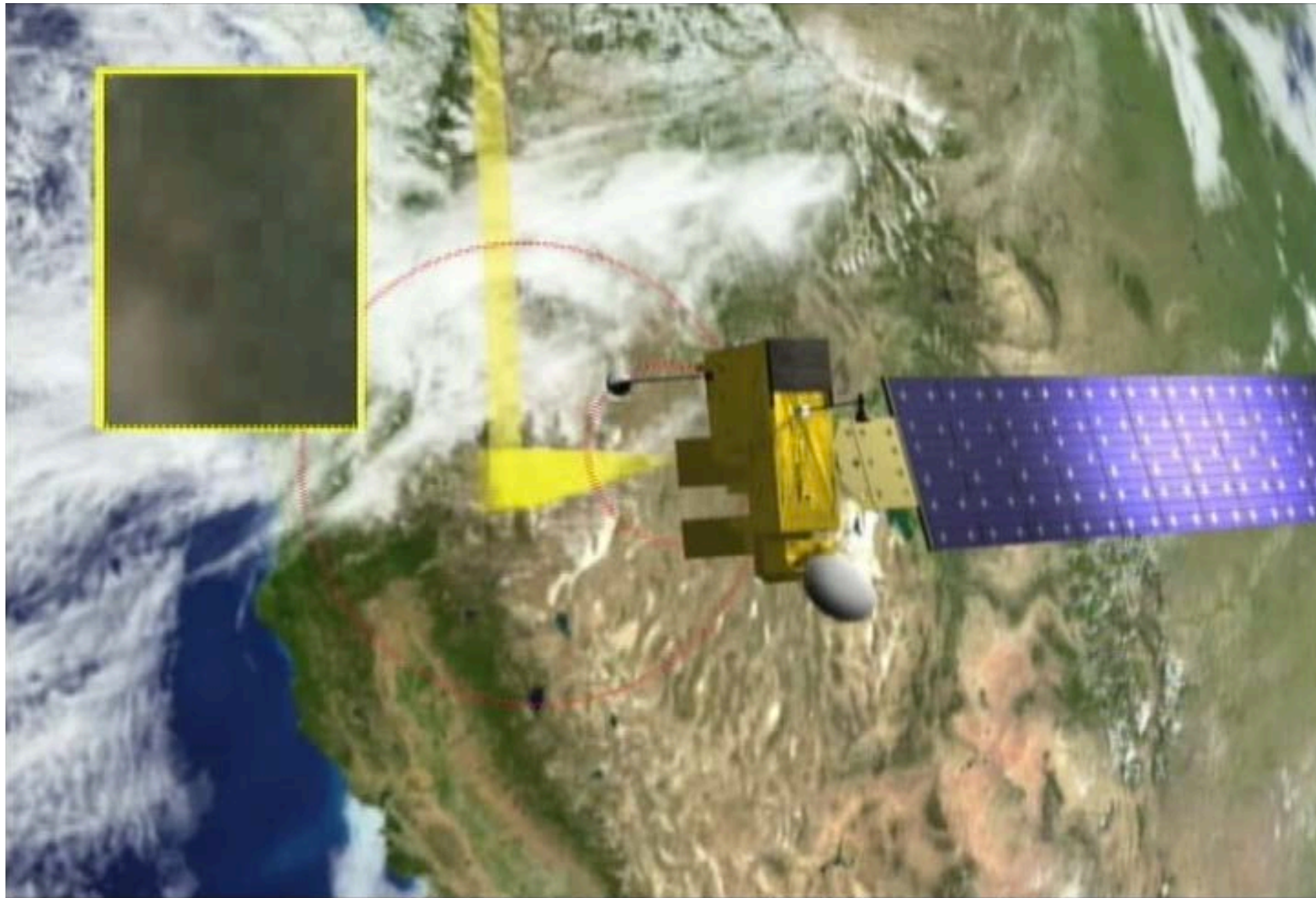
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In 2004, AI in Space becomes a reality

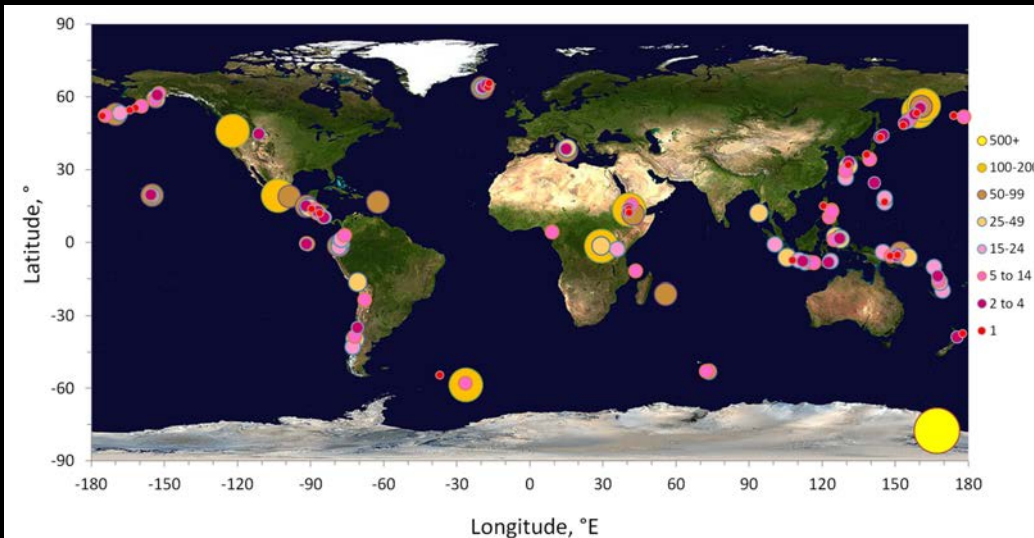
Autonomous Scienceraft AI Software operates the EO-1 spacecraft for over a dozen years, acquiring over 60,000 images, issuing almost \$3 million commands



Simultaneously the Earth Observing Sensorweb links together scores of spacecraft, ground observatories, and air and marine assets to monitor volcanos, flooding, wildfires and more, acquiring thousands of images without any human intervention!

Example: NASA ASE/EO-1 Volcanoes

- Automated tasking: Volcano Sensorweb
 - Links together scores of space, ground, other assets
 - Automated Data analysis, triage to generate prioritized requests → ASE/EO-1 service → products delivered to stakeholders.
 - Over 100,000 alerts/triggers
- End Result, - Thousands of volcanic scenes 2008-2017,
35%+ of said scenes with thermal signatures!
Compare to MODIS background < 1% of scenes with active thermal signature.



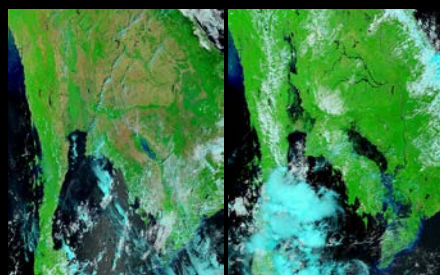
Partners (incomplete list):

MODVOLC
GOESVOLC
AFWA
VAAC
Iceland/MEVO
Etna VO (U. Firenze)
MEVO (NM Tech)
HVO (Kilauea)
IEGPN (Ecuador)
CVO (Mount St. Helens)

See [Chien et al. 2005 IEEE IS, Davies et al. 2006 EOS, Davies et al. 2005, 2007, 2016a,b]

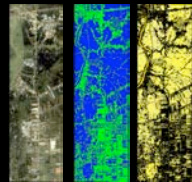
Example: NASA ASE/EO-1 Flooding

- Automated tasking: Thailand Flood Sensorweb
 - Links together space, ground assets
 - Automated Data analysis, triage to generate prioritized requests
 - ASE/EO-1 observation service and others
 - products to stakeholders
 - Fuse data from satellite, ground sensor, and model sources
- +100% temporal coverage for 2010-2011, 2011-2012 Flooding Seasons

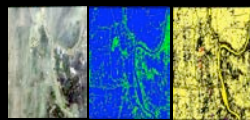


Dry: March 6, 2011

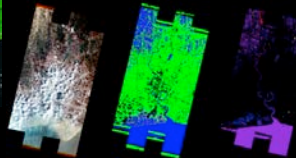
Flooded: October 27, 2011



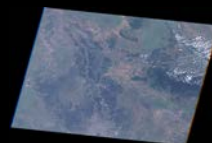
Ikonos



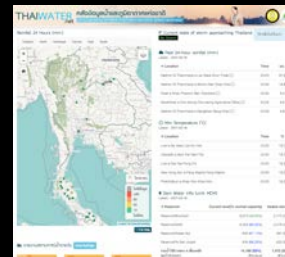
GeoEye-1



EO-1/ALI



Landsat-7 ETM



In-situ data and Model

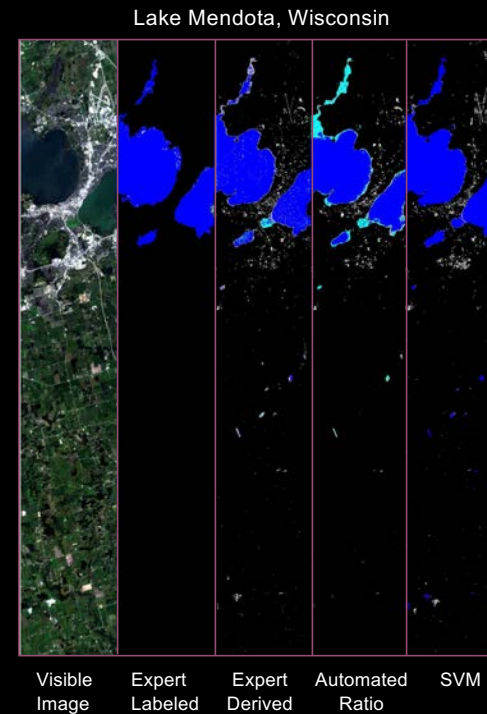
Partners:
HAII (Thailand)
Digital Globe
(Worldview)
Geo-Eye
Radarsat
Landsat
LANCE-MODIS

See [Chien et al. 2011 IGARSS, 2013 JSTARS].
See also Wildfires [Chien et al. 2011 JSTARS, Chien et al. JAIS 2018]

Land, Ice, Water, Snow Detection using Support Vector Machines

- Primary Purpose
 - Identify areas of land cover (land, ice, water, snow) in a scene
- Three algorithms:
 - Scientist manually derived
 - Automatic best ratio
 - Support Vector Machine (SVM)

Classifier	Expert Derived	Automated Ratio	SVM
cloud	45.7%	43.7%	58.5%
ice	60.1%	34.3%	80.4%
land	93.6%	94.7%	94.0%
snow	63.5%	90.4%	71.6%
water	84.2%	74.3%	89.1%
unclassified	45.7%		

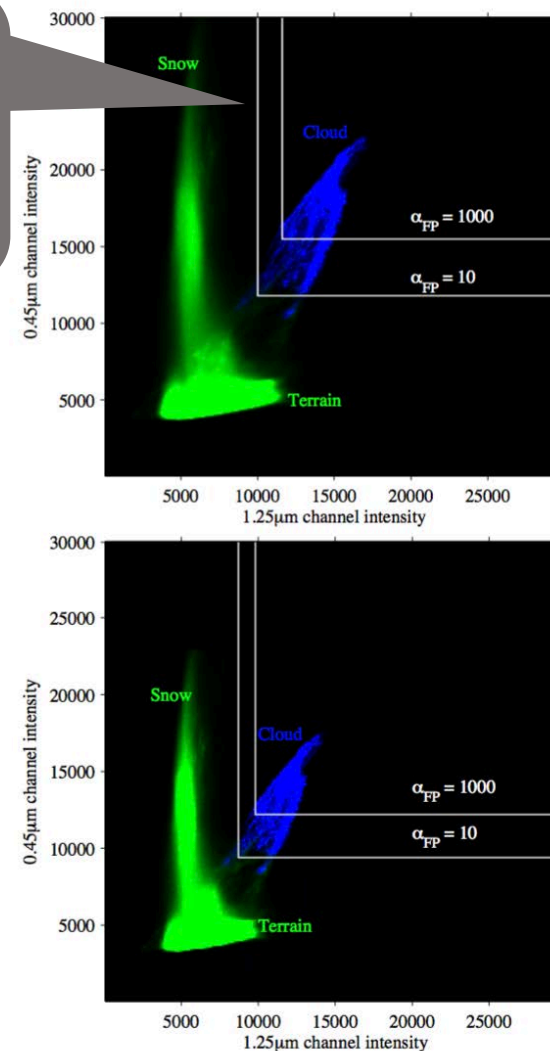


Bayesian Thresholding

Bayesian thresholding exploits the natural division between dark surface materials and bright cloudy regions at particular wavelengths.

- While the RDF method examines a window of values around the pixel to be classified, BT classifies each pixel independently.
- BT was previously employed to analyze data collected by the AVIRIS-C airborne sensor (Thompson et al. 2014).
- For EO- 1, BT used Hyperion bands at 447, 1245, and 1658 nm to span the range from blue to short-wave infrared.

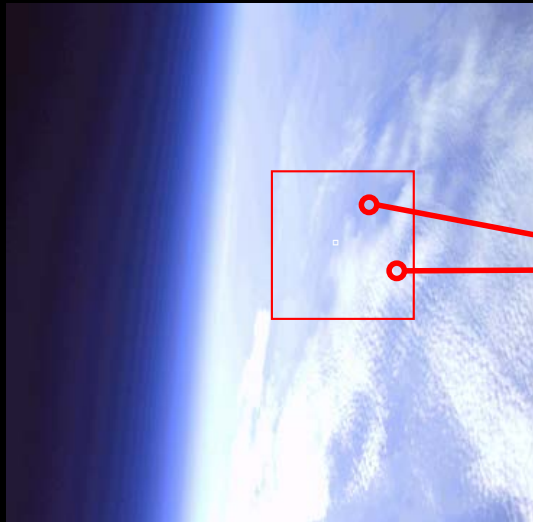
Image courtesy Thompson et al. 2014
TGARS



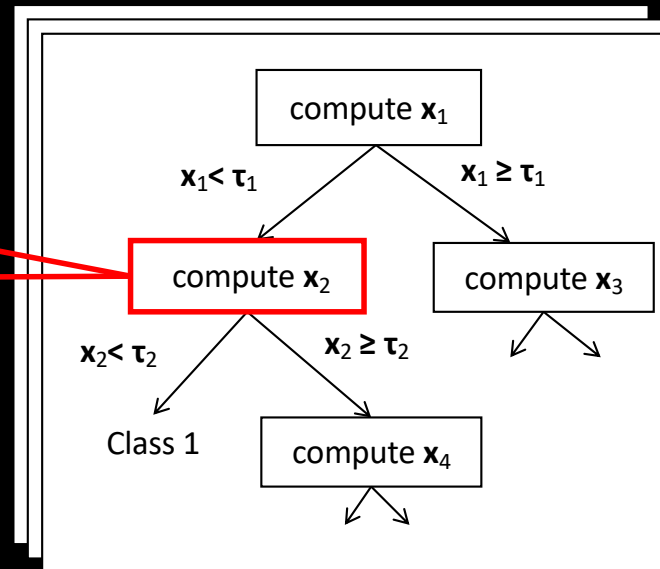
TextureCam – Random Decision Forests

Pixel classification for cloud screening,

Pixel to be classified

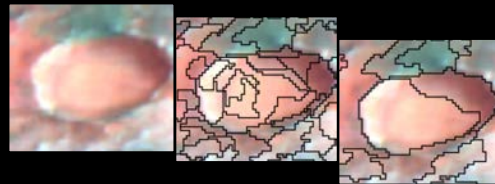


Random forest classifier



[Thompson et al., i-SAIRAS 2012; Wagstaff et al., *GRL* 2013; Bekker et al., *Astrobiology* 2014]

Onboard Hyperspectral Analysis



Superspixel segmentation

+

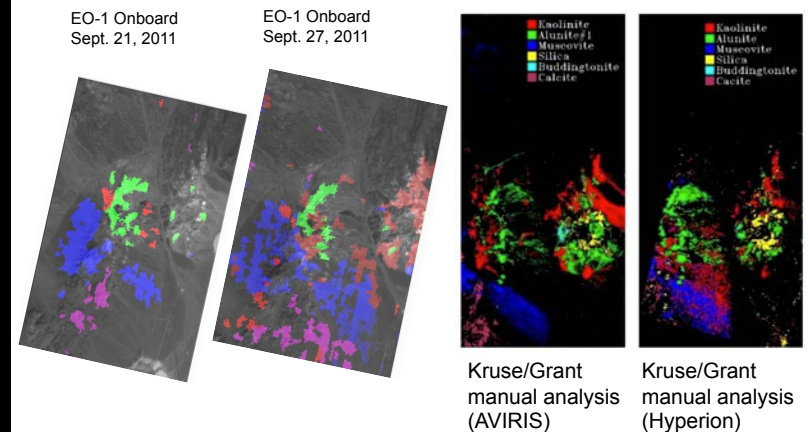
The sequential maximum angle convex cone
(SMACC)

endmember extraction

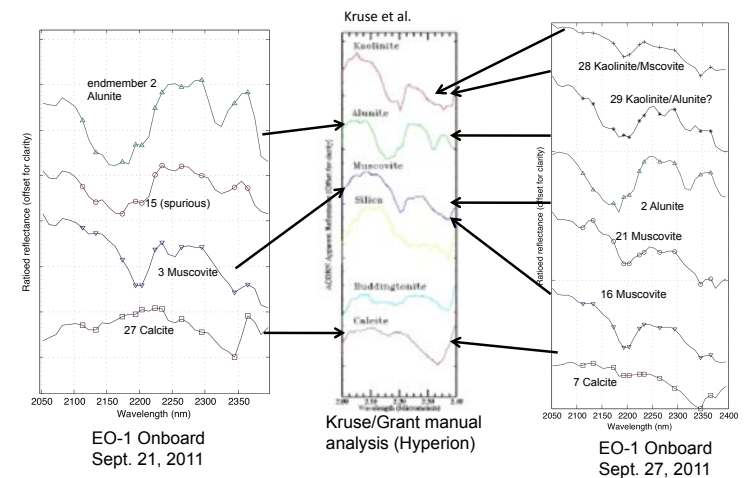
Results from onboard EO-1 (9/2011)

D. Thompson et al. 2012 TGARS

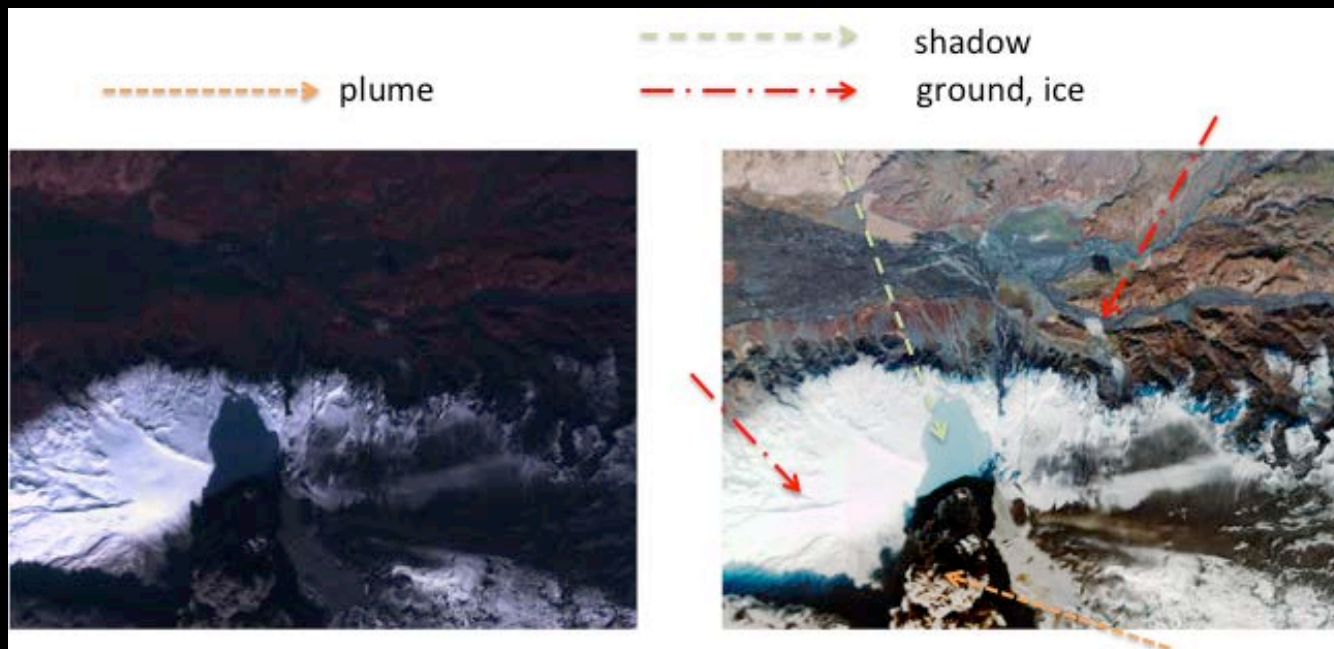
Repeatability: maps



Repeatability: detections



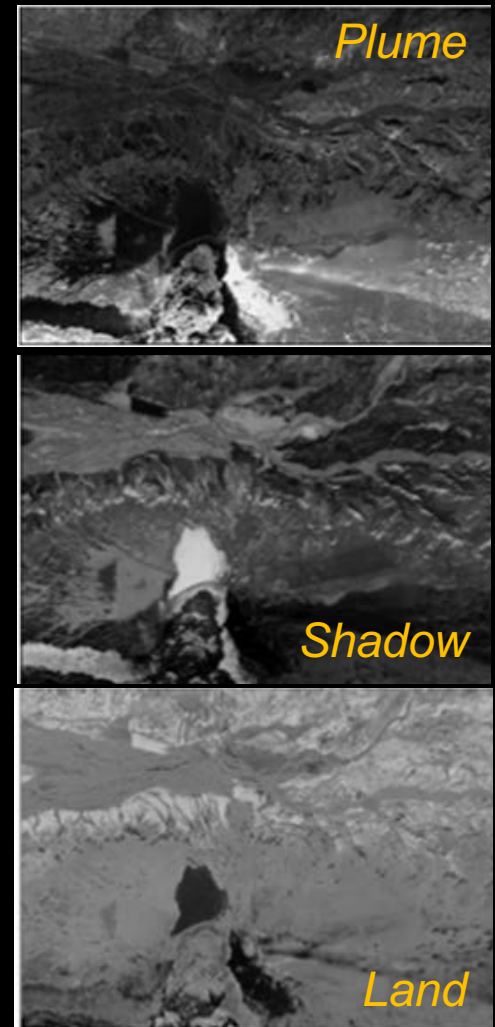
WorldView-2 Data



*WorldView-2 Image of
Eyjafjallajökull eruption, acquired
April 17, 2010*

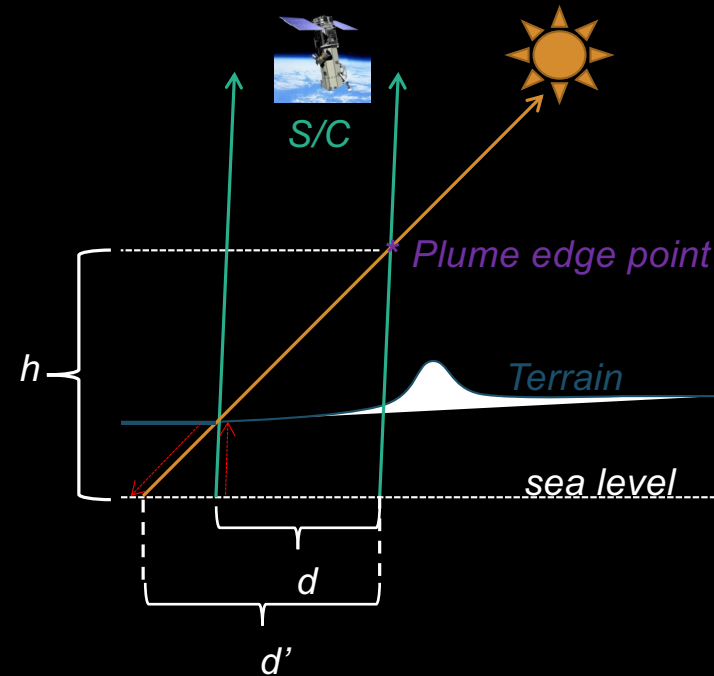
Mclaren et al. 2012, SPIE

Histogram-equalized image



Height Estimation

- Estimate plume height from shadows
- Followed calculations derived in A. J. Prata and I. F. Grant, "Determination of mass loadings and plume heights of volcanic ash clouds from satellite data"
- Rotated classification maps so sun rays are coming from $-Y$ axis (bottom of the image)
- Collected shadow line segments which have a neighboring plume region in sunward direction
- Corrected shadow lengths for:
 - Sun and spacecraft azimuth, elevation
 - Ground elevation at shadow edge
 - ASTER GDEM2 DEM
 - 30m horiz. spacing, 1m vert.



d : Initial shadow length

d' : Shadow length after projecting up to DEM & down along sun vector

h : Plume point height

Saliency – Unsupervised Novelty Detection

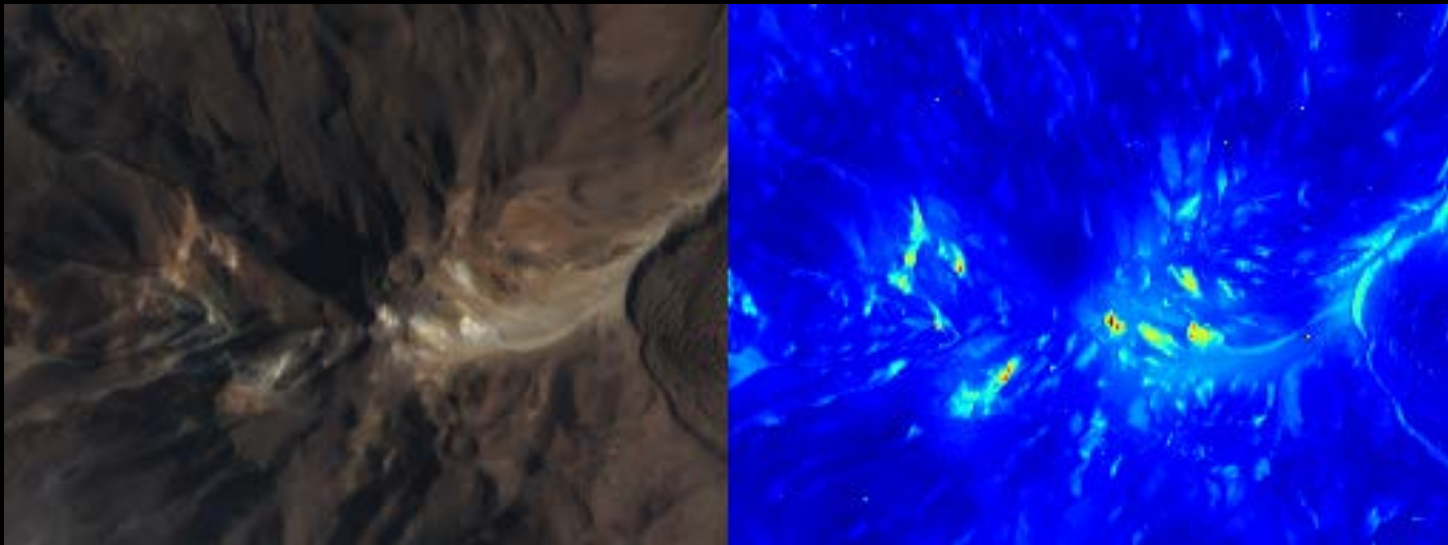
- Saliency is an unsupervised algorithm that assigns a score to each pixel that captures how anomalous it is within its local context. The saliency S of pixel p is computed with respect to the histogram P_w of intensity values in the surrounding window w :

$$S(p, w) = \frac{1}{M} \sum_i |p - i| P_w(i)$$

- where M is a normalization factor that is the maximum
- saliency possible given the window histogram and size:

$$M = N(N - 1) \sum_i P_w(i)$$

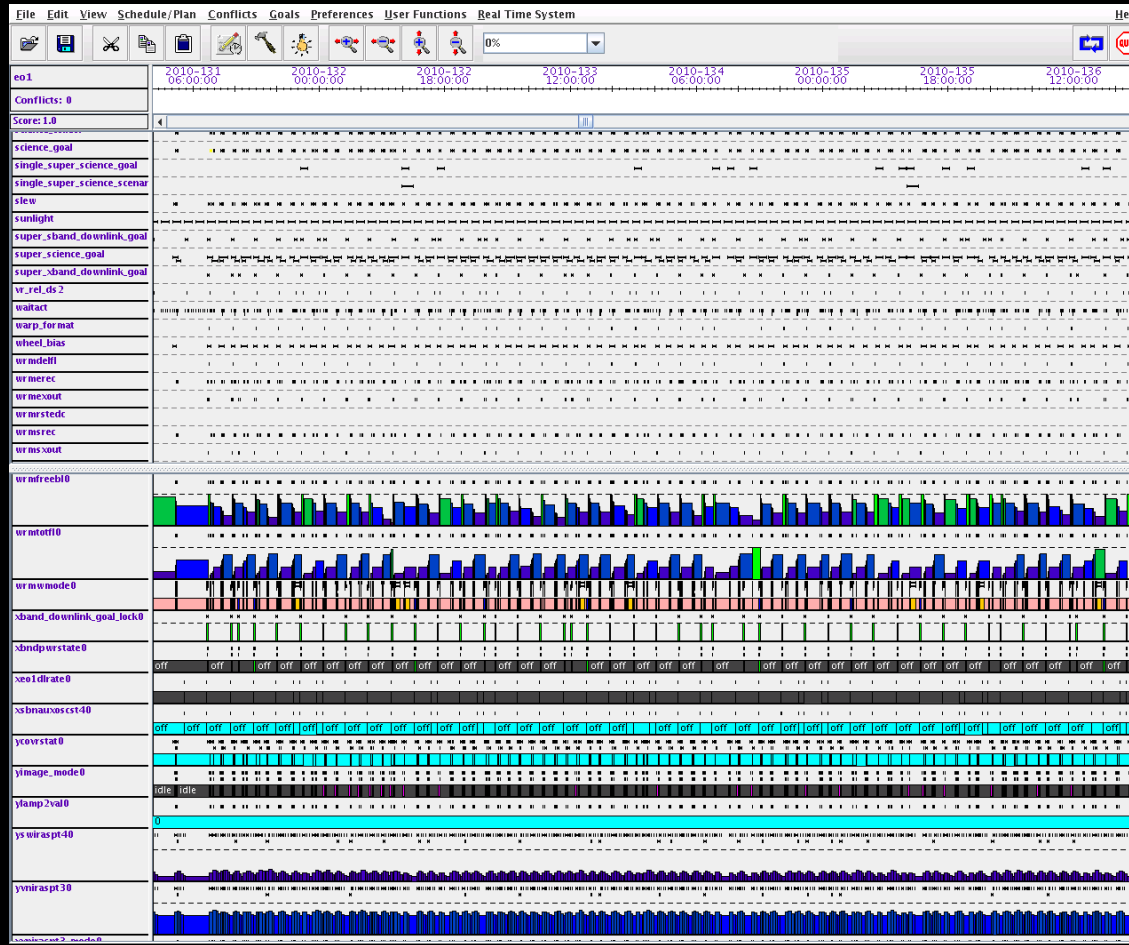
Salience for Volcano in Chile



Salience for buildings in Thailand



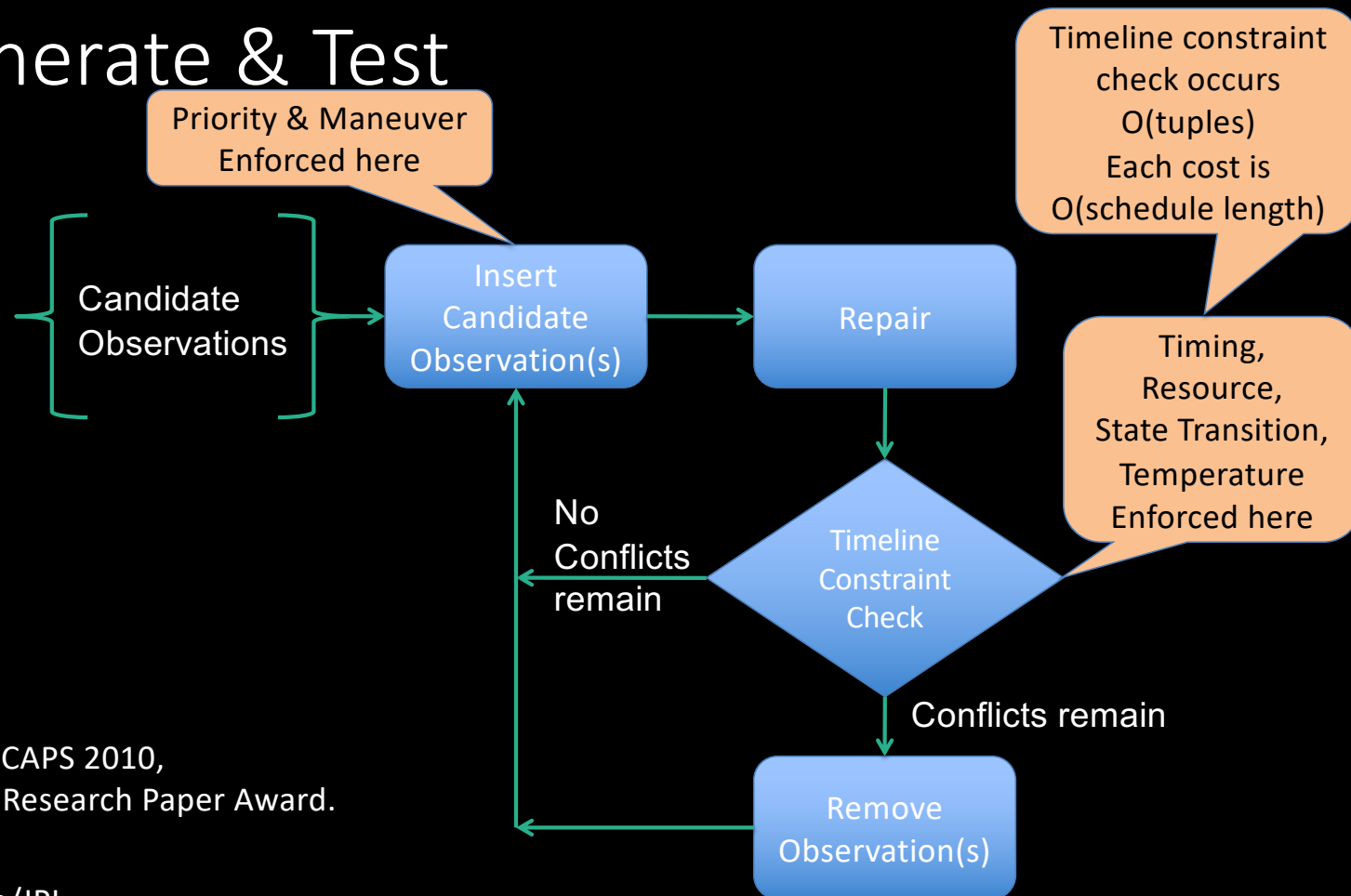
Timeline-based Scheduling



Many timeline based schedulers in use for space missions.

See
[Chien et al. 2012,
SpaceOps]

Generate & Test



See:
Chien et al., ICAPS 2010,
Best Applied Research Paper Award.

POC: S. Chien/JPL

SHARE

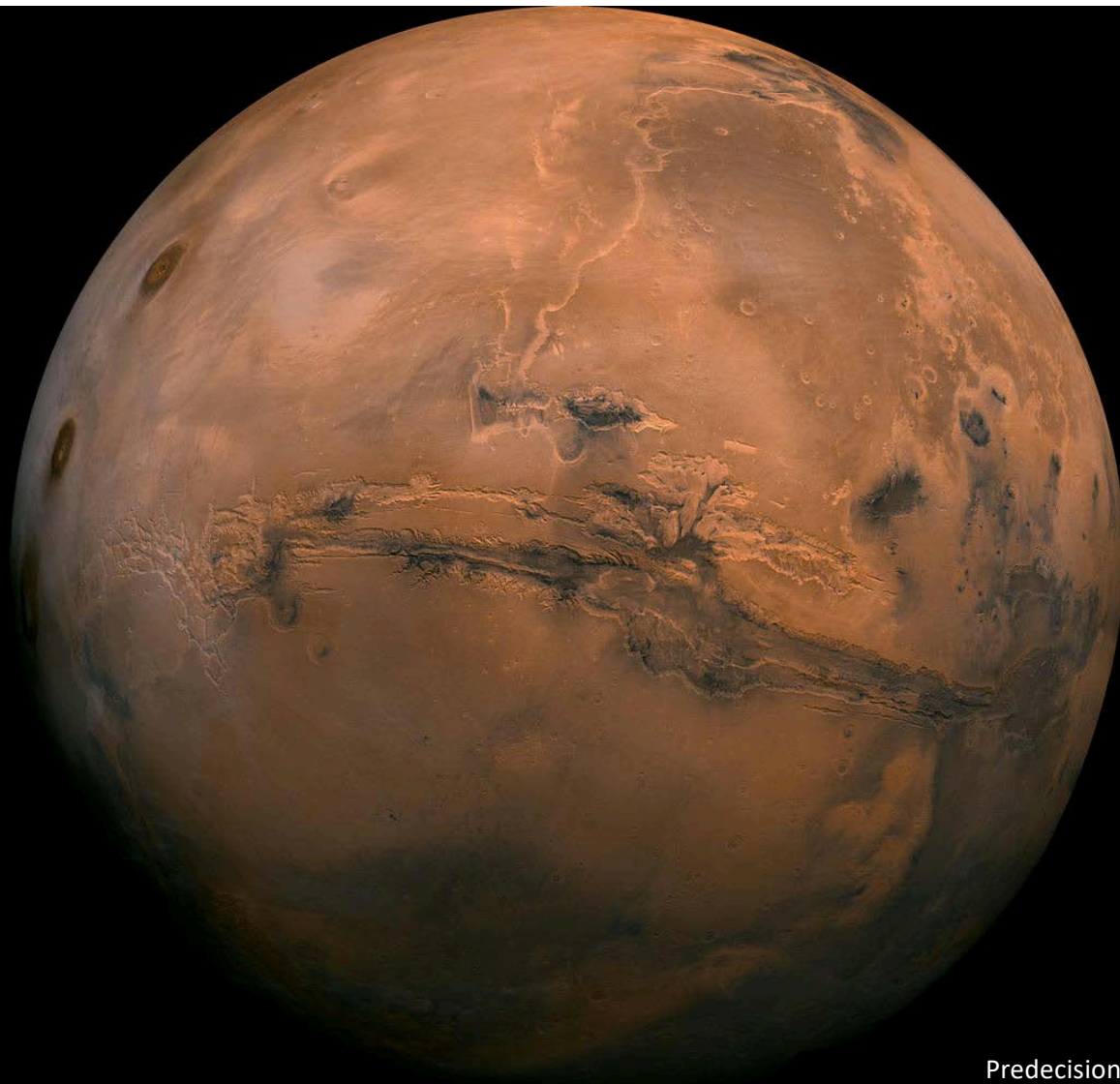


2337

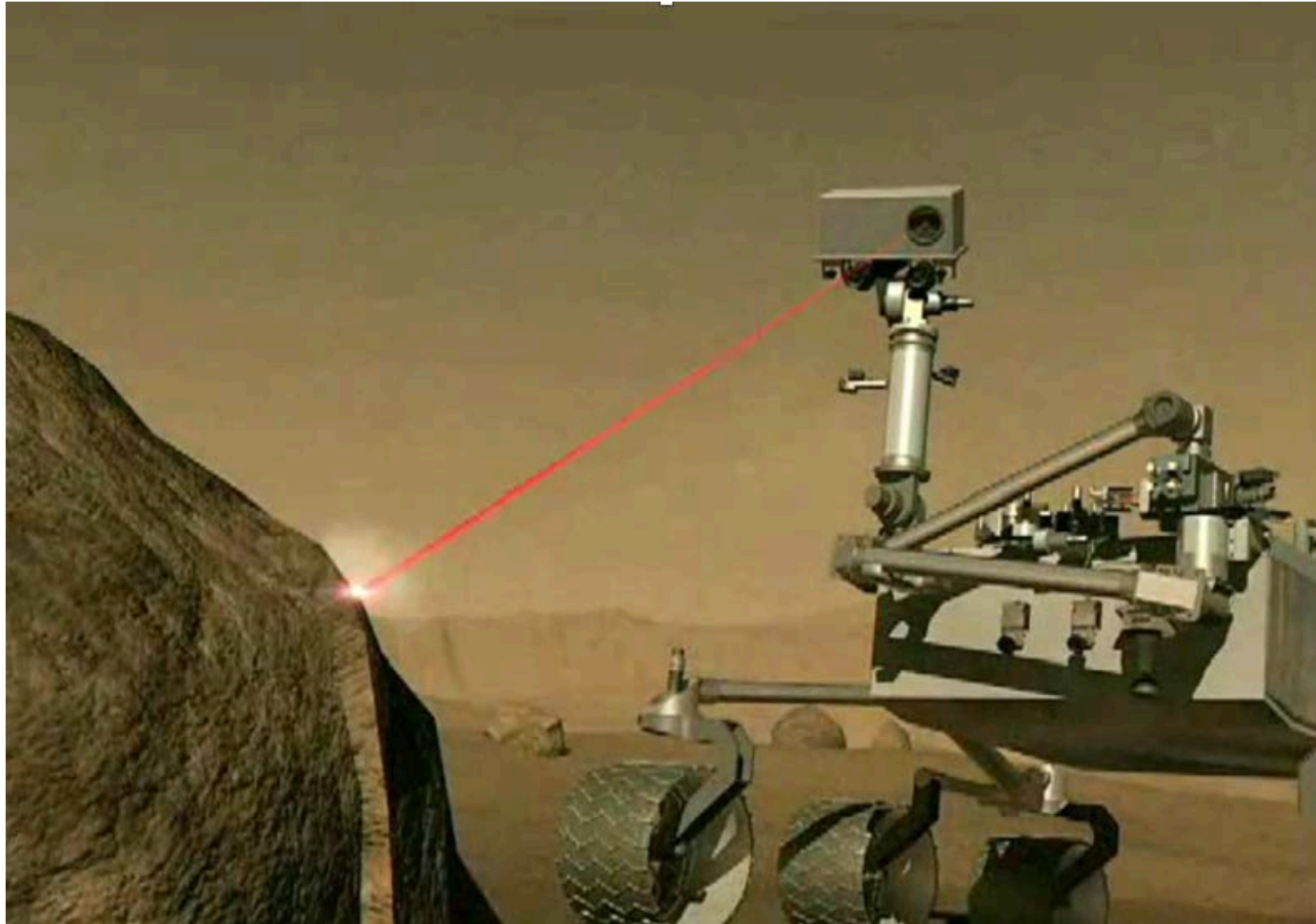


Manam Volcano viewed from EO-1 on June 28th 2010  ALAMY

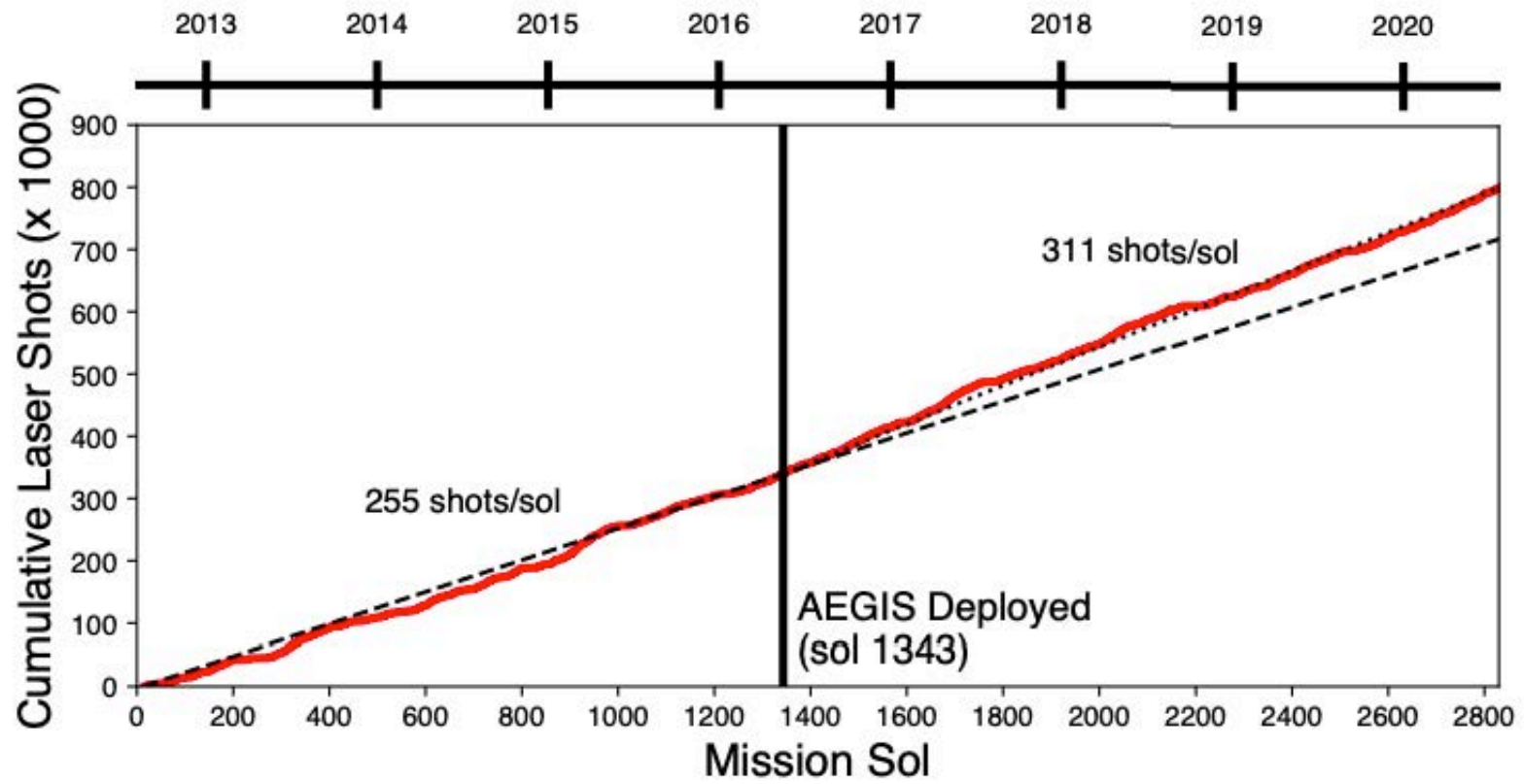
<https://www.wired.com/2017/03/say-farewell-eo-1-nasas-smartest-satellite/>



Predecisional, for planning and discussion only.



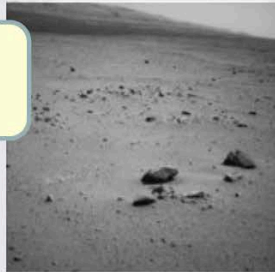
AI-based Targeting
of the Chemcam
laser on the Mars
Science Laboratory
Rover



OASIS

Onboard Process for MSL

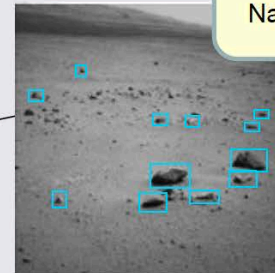
Image pointing determined by ground.



Navcam or RMI acquisition

Target detection

Detection of rock candidates in Navcam image.



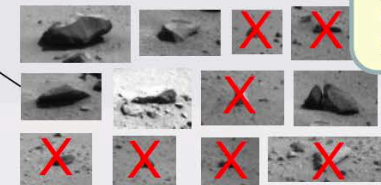
Quantification of key target properties such as intensity, size, shape, and distance from rover.



Target feature extraction

Target filtering

Ops can filter targets based on size, distance, etc.



Target prioritization

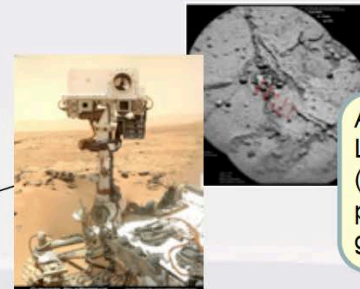
Ops can prioritize important properties for each run



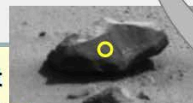
Determine center target position

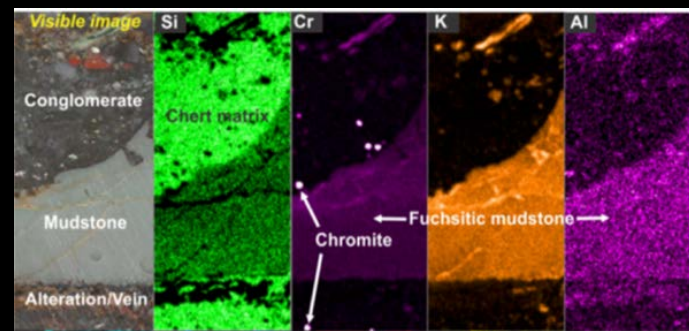
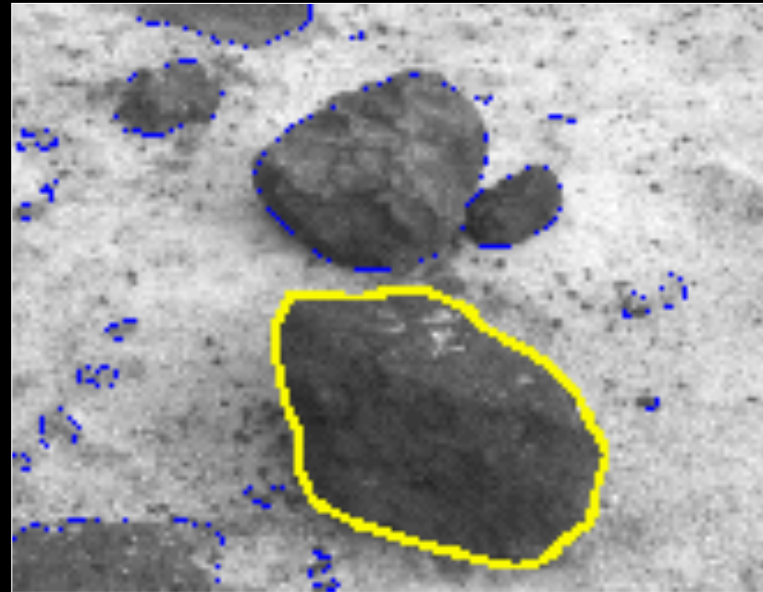
CCAM raster acquired

Acquire ChemCam LIBS raster of target (size and direction pre-specified by ground)



Can repeat for multiple targets





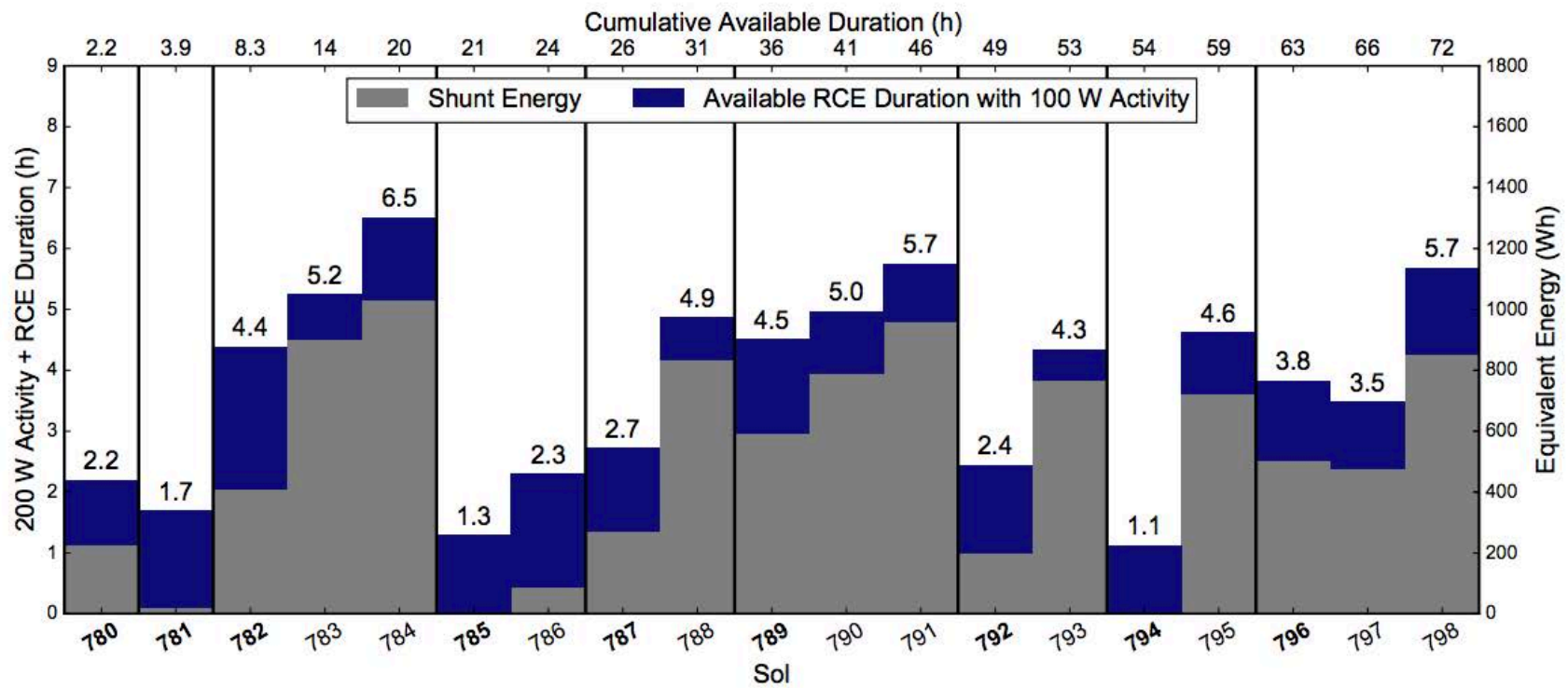
POC: T. Estlin, R. Francis/JPL
 AEGIS/MER, winner of the 2011 NASA Software of the Year Award

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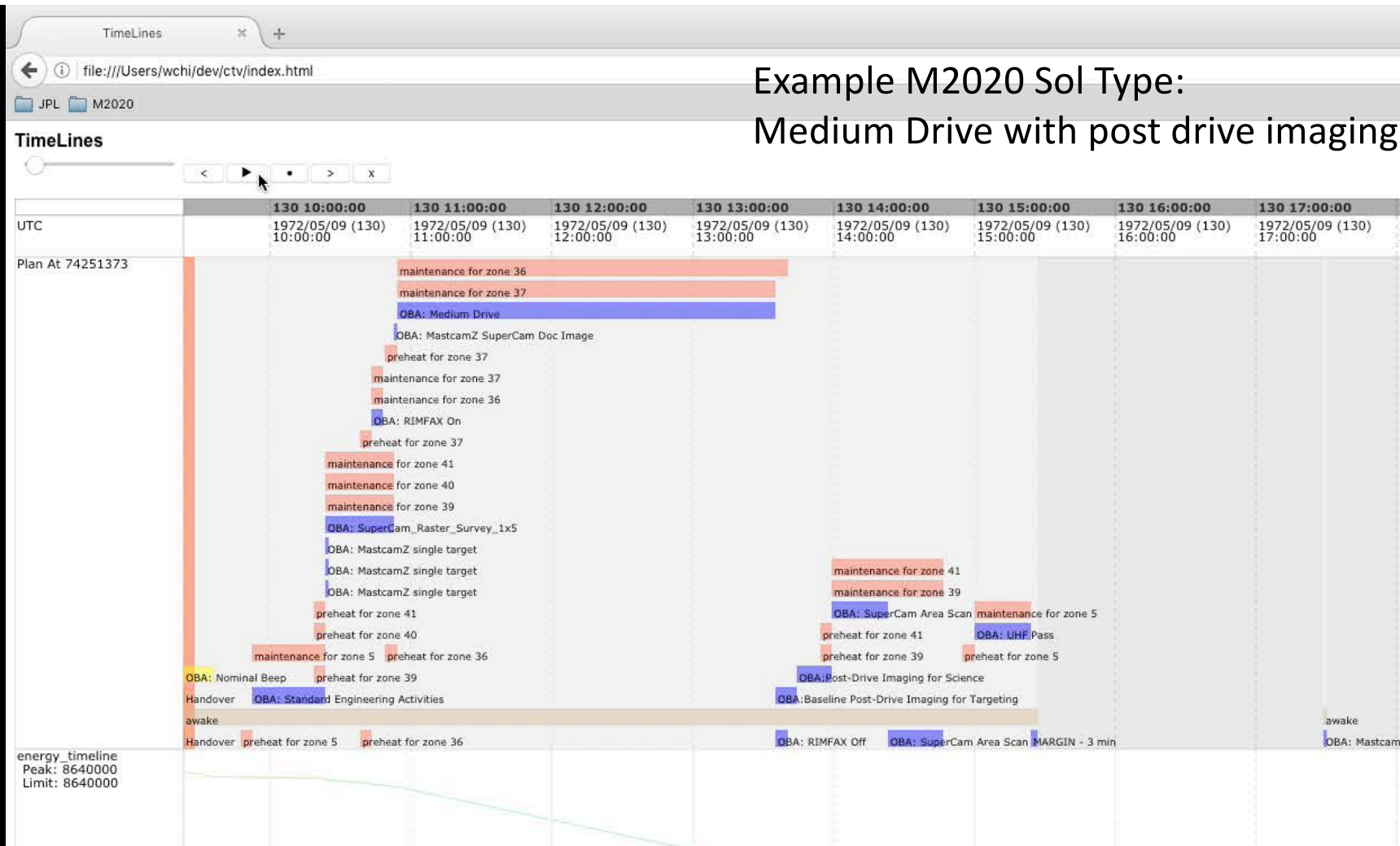
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MSL unused Time/Energy



MSL submasters on average execution time 28% less than planned time (+ cleanups)

Example M2020 Sol Type: Medium Drive with post drive imaging

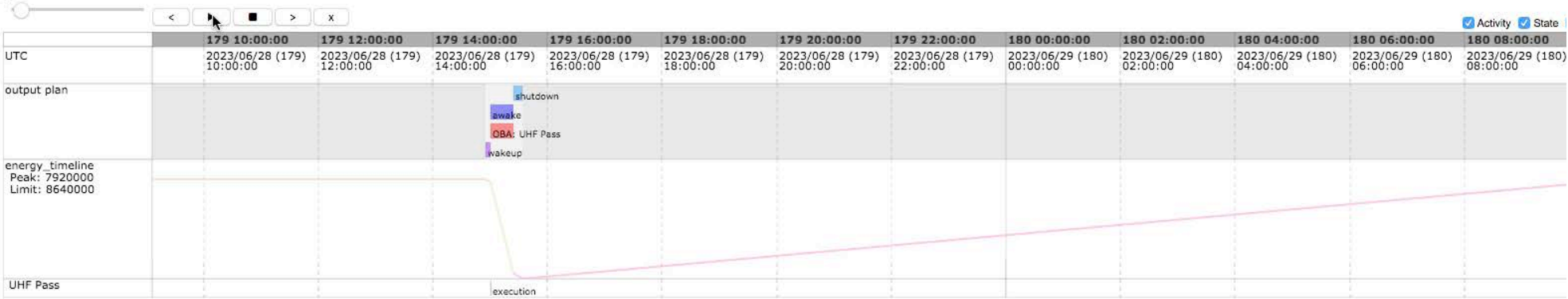


Rabideau et al. 2017 IWPSS; Chi et al 2018 ICAPS; Chi et al. 2019 ICAPS POC: S. Chien/JPL

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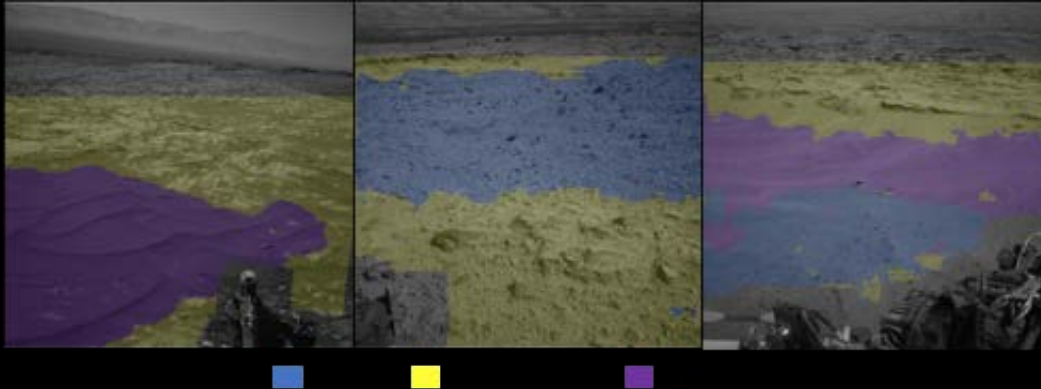
plan1





Future AI

Self Reliant Rover demonstrated an 80% reduction in time to complete a walkabout campaign [Gaines et al. 2020] by using onboard science driven AI. Technologies also very relevant to "long drive" scenarios.



Automated terrain (slip) analysis assists ground-based MSL rover planners more quickly and accurately plan rover paths [Ono et al. 2020].

		Predicted			
		Soil	Bedrock	Sand	Big Rock
Actual	Soil	96.00	0.31	3.69	0
	Bedrock	6.15	90.87	2.54	0.44
	Sand	0.25	3.23	96.51	0.01
	Big Rock	11.67	0.03	5.48	82.83

Table 3: MSL *NAVCAM-Random* confusion matrix percentages calculated with respect to the 3 label agreement test set. Overall accuracy is 94.97%.

		Predicted			
		Soil	Bedrock	Sand	Big Rock
Actual	Soil	99.10	0.32	0.57	0.01
	Bedrock	3.64	94.90	0.37	1.09
	Sand	0.88	5.62	93.45	0.05
	Big Rock	6.76	0	0	93.24

Table 4: MSL *NAVCAM-Merged* confusion matrix percentages calculated with respect to the 3 label agreement test set. Overall accuracy is 96.67%

Future rover missions can use this technology onboard to enable more capable slip-aware autonomous driving [Gaines et al. 2020].

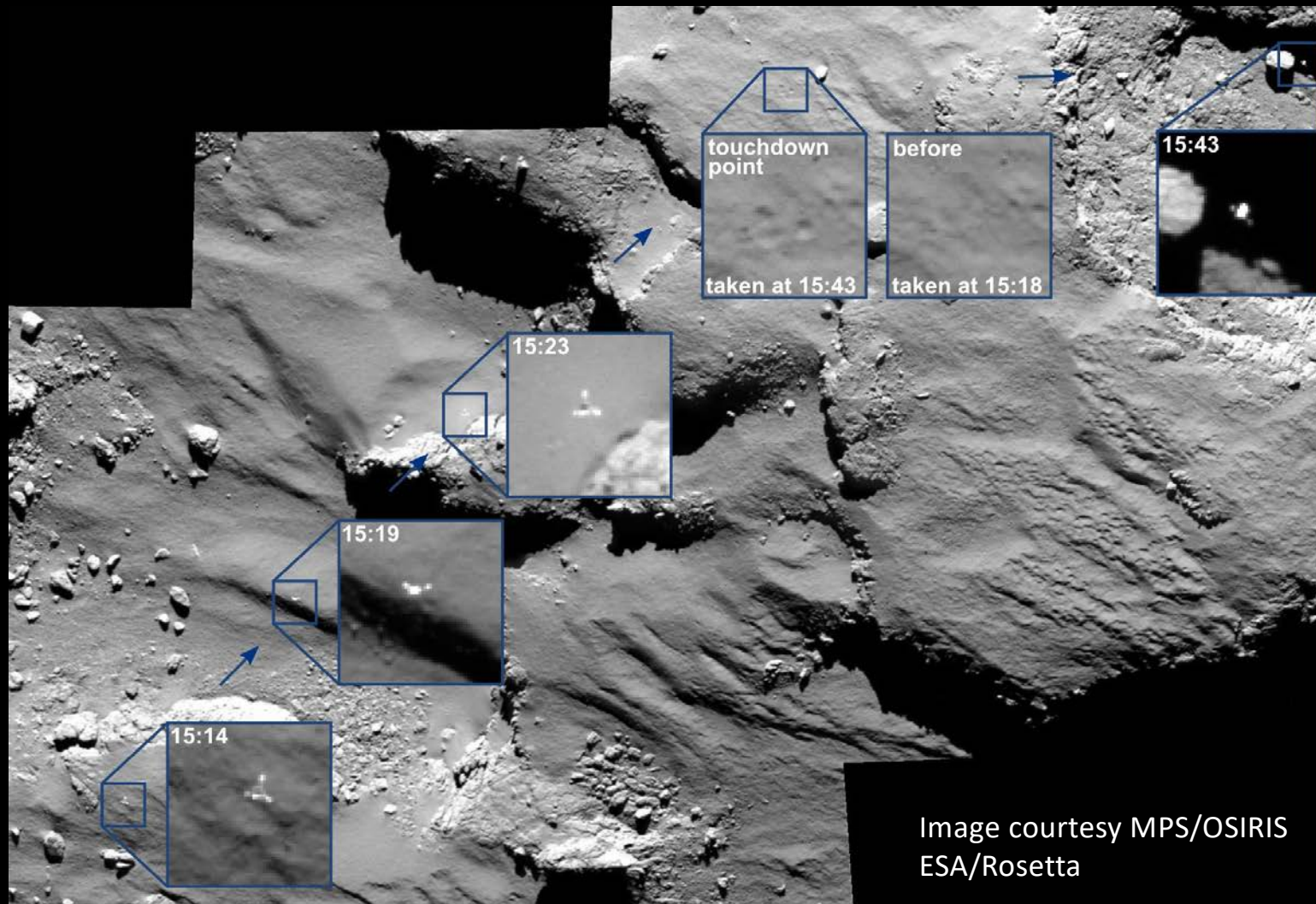
Rosetta

Philae Lander Delivery

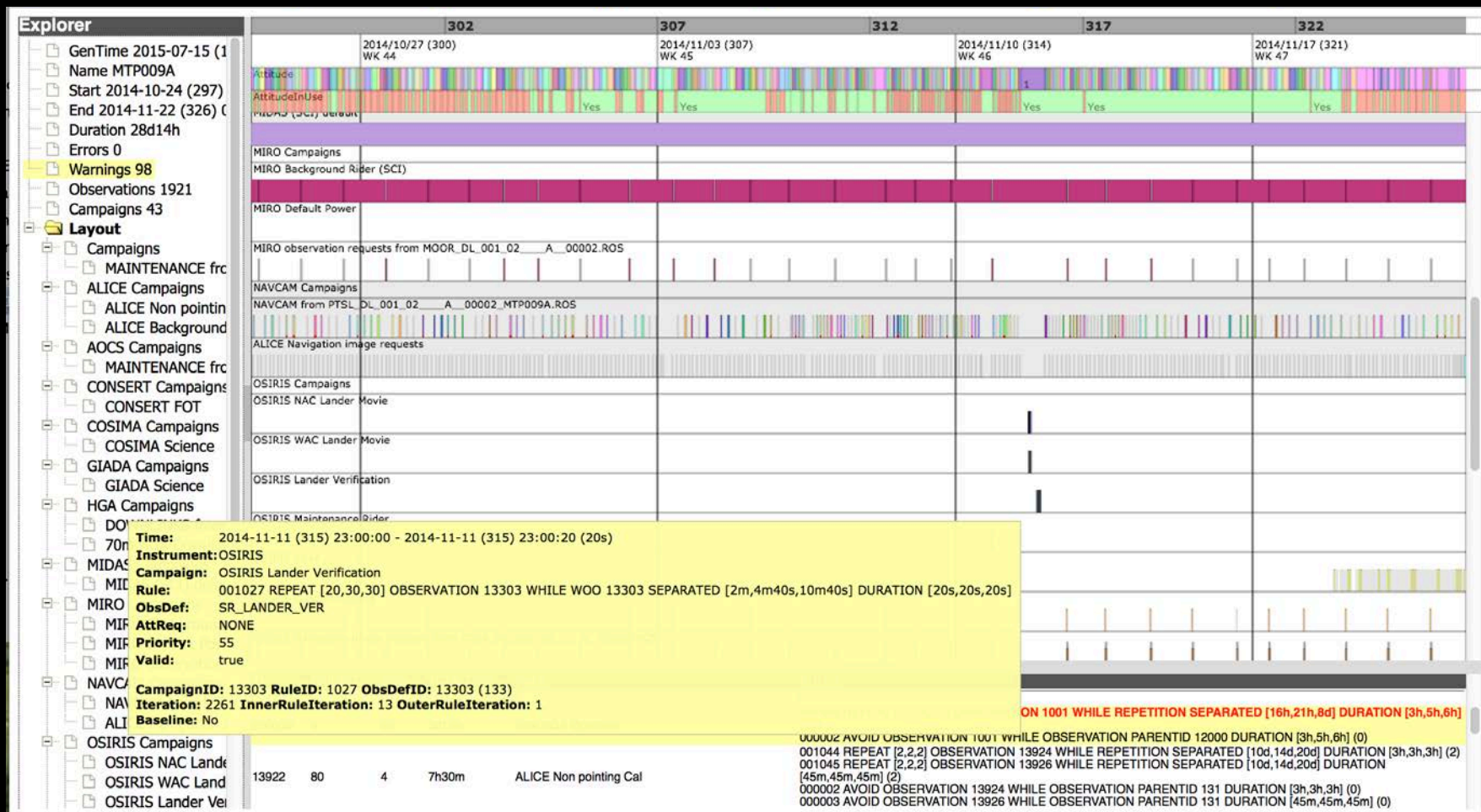


Image courtesy MPI/OSIRIS, ESA/Rosetta

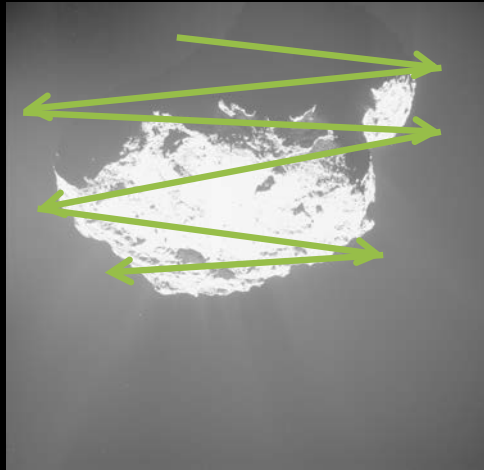
Lander Delivery



Lander Delivery



Broad Sweeps vs Targeted Sweeps

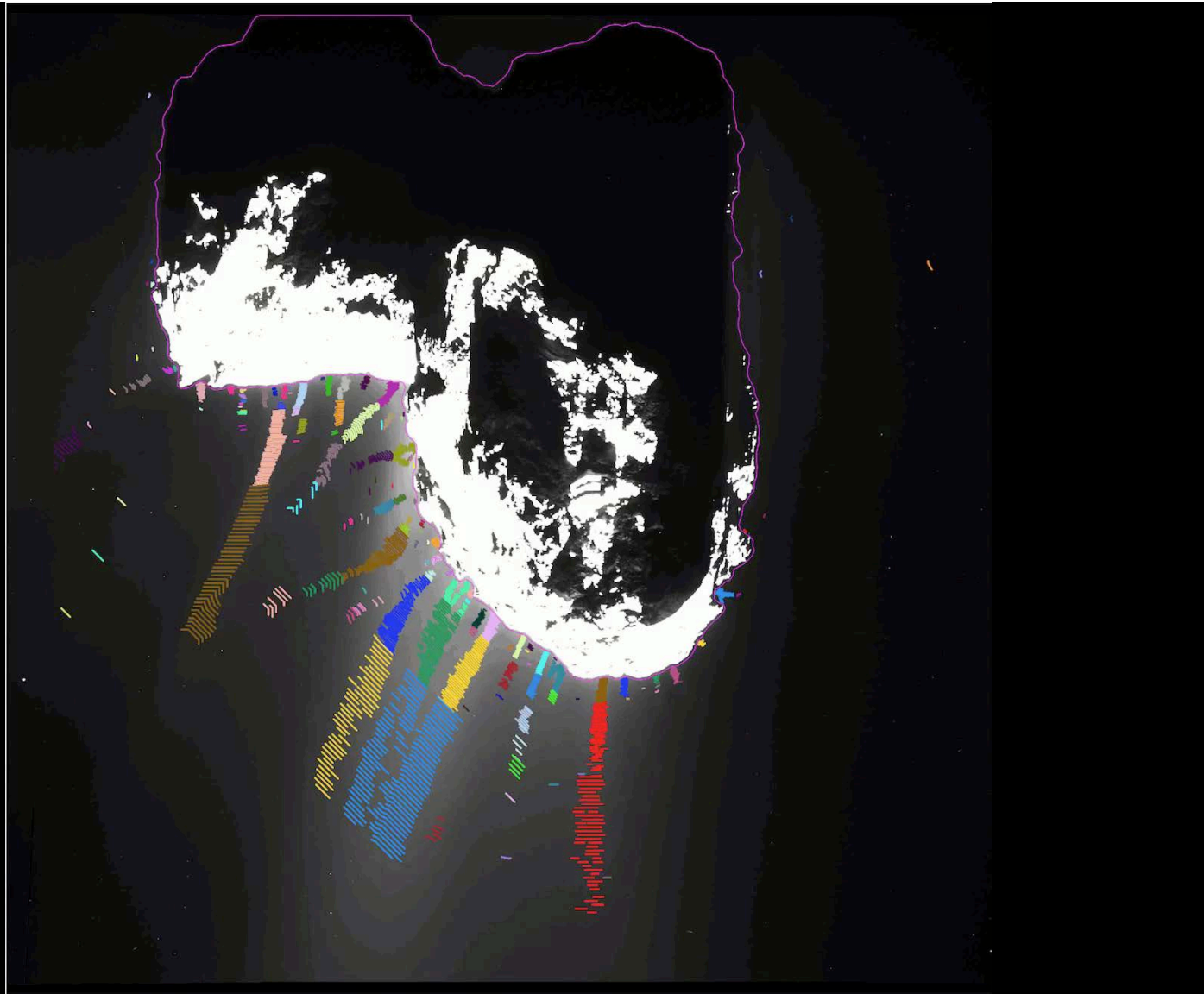


Plume Detection Rosetta OSIRIS

Brown et al. 2019 *Astronomical J.*

Collaboration w. H. Sierks/MPI

Original Image sequence credit:
OSIRIS/MPI, Rosetta/ESA



Coverage Scheduling

- Numerous missions involve variations of coverage scheduling, this technology is mature and in use for several NASA missions
 - ECOSTRESS: coverage, illumination, priority and background mapping, radiation keepouts, data management
 - OCO-3: visibility, illumination, complex geometry, area map prioritization, PMA calibration, complex rapid pointing and flip constraints
 - NISAR: data volume, power/energy, complex coverage campaigns

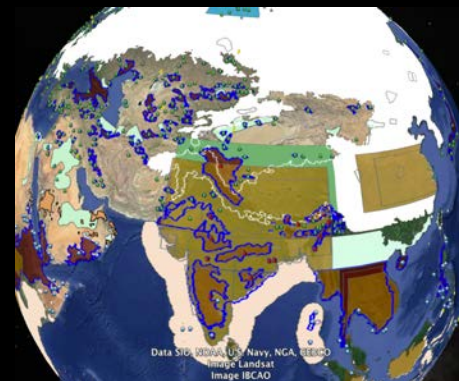
ECOSTRESS

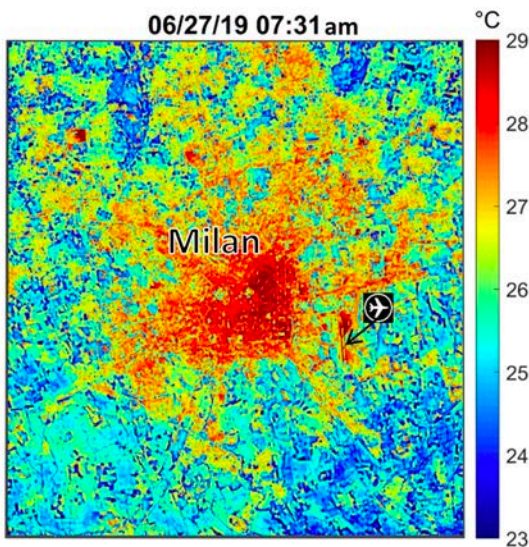
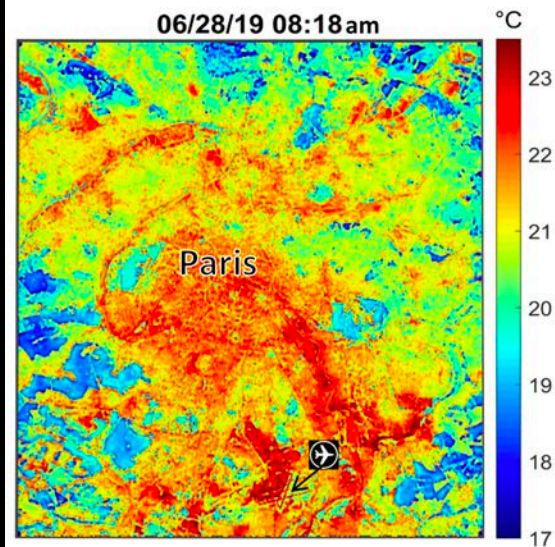
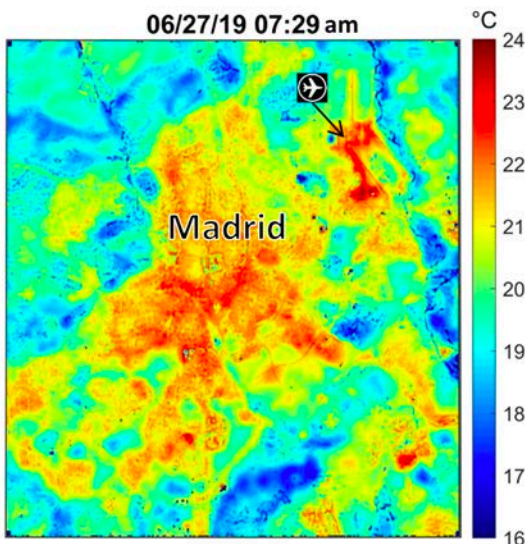
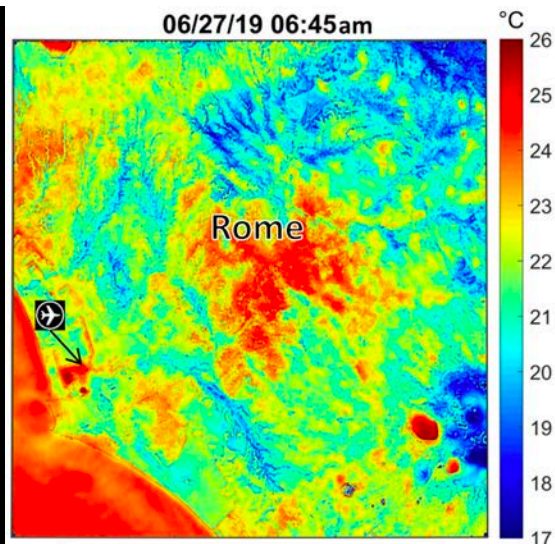


OCO-3



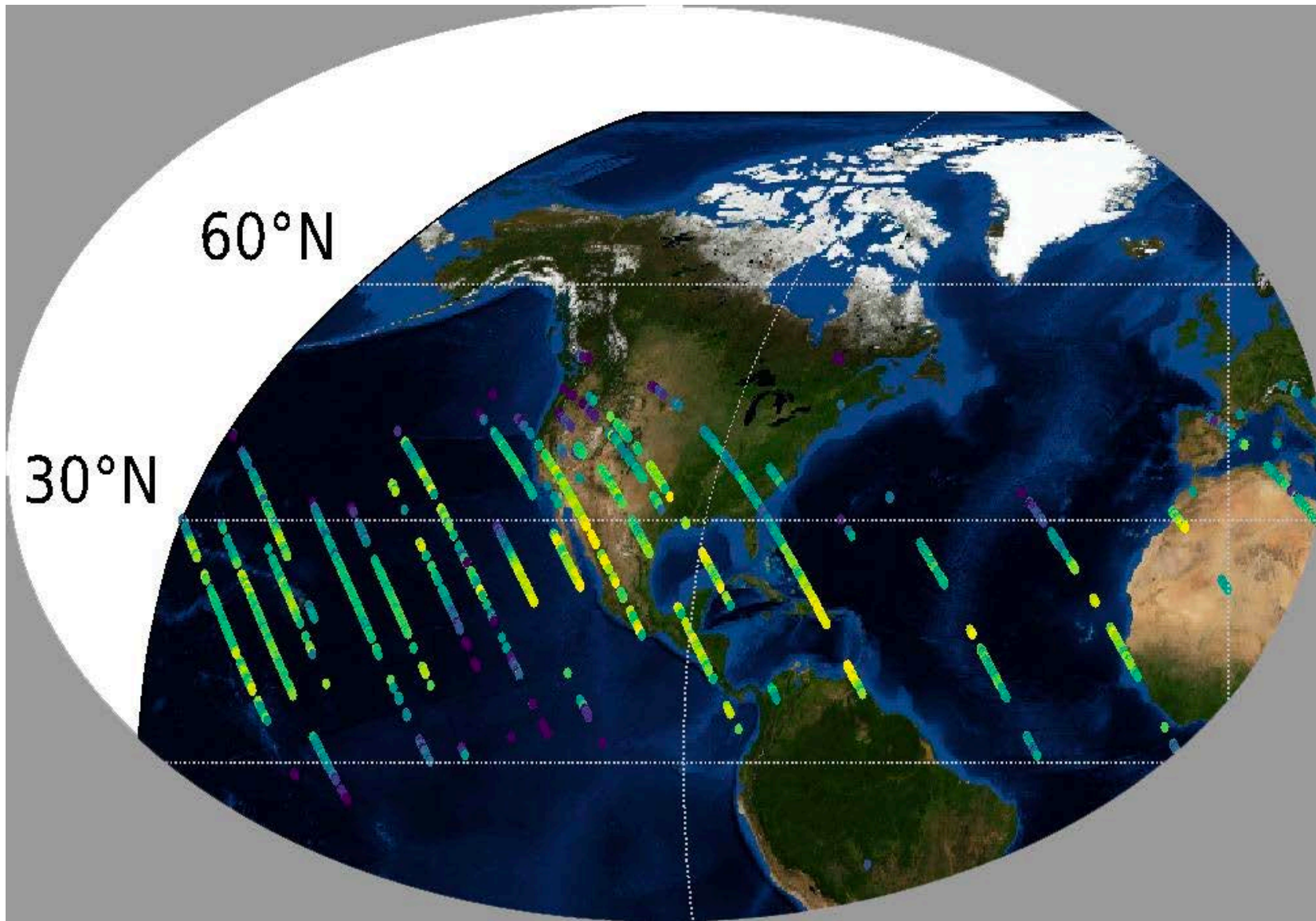
NISAR





NEWS | JULY 2, 2019
NASA's ECOSTRESS Maps
European Heat Wave From
Space

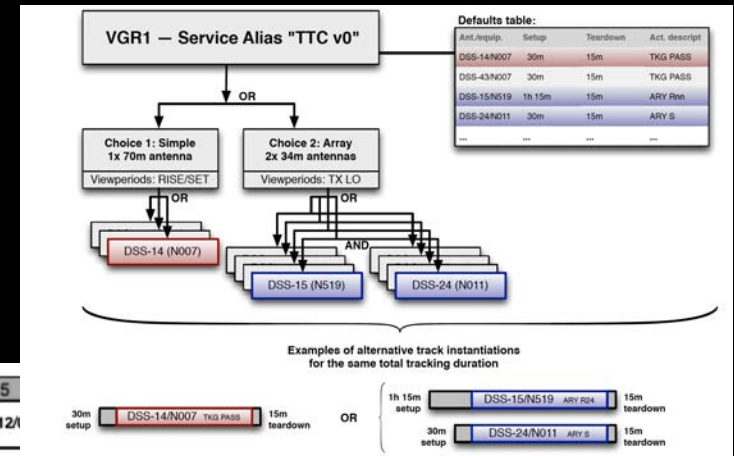
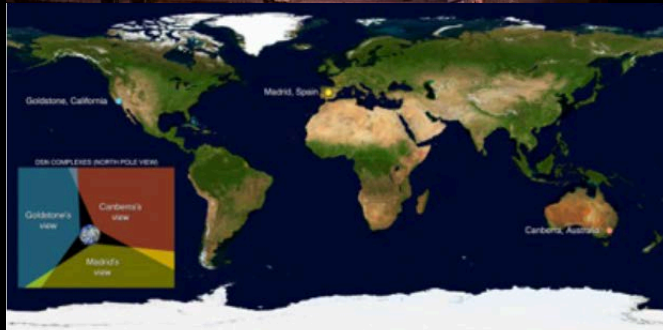
<https://www.jpl.nasa.gov/news/news.php?feature=7445>



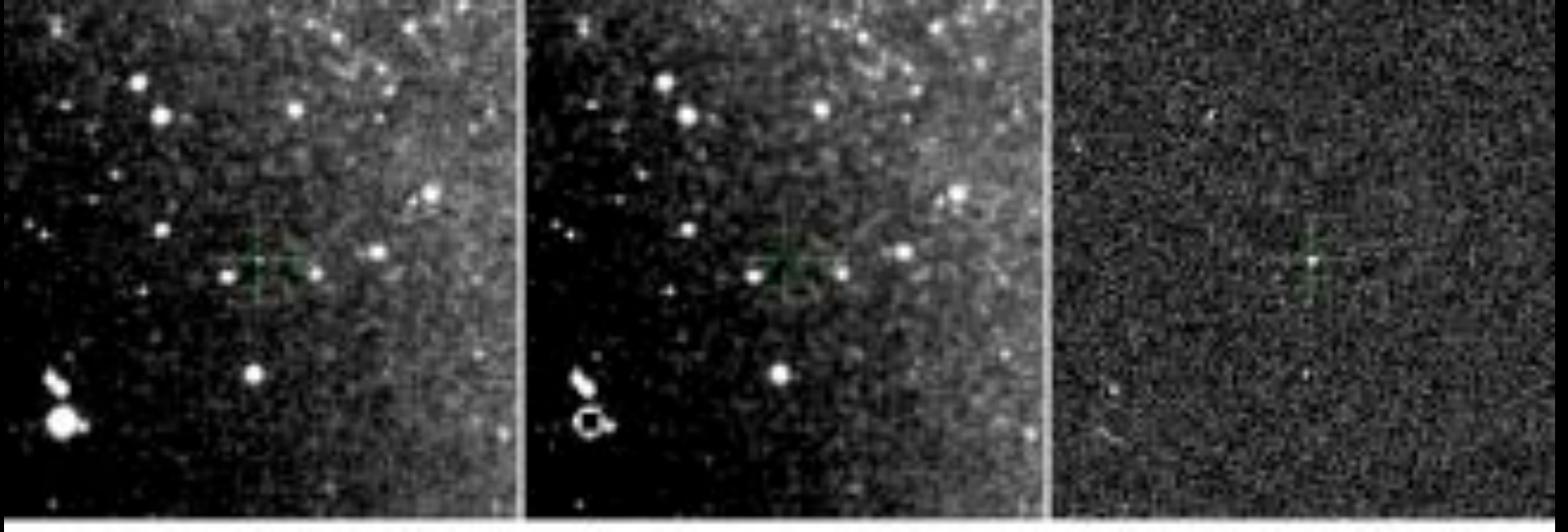
NEWS | JULY 12, 2019
NASA's Orbiting Carbon Observatory-3 Gets First Data

<https://www.jpl.nasa.gov/news/news.php?feature=7452>

No time for...ask me about...

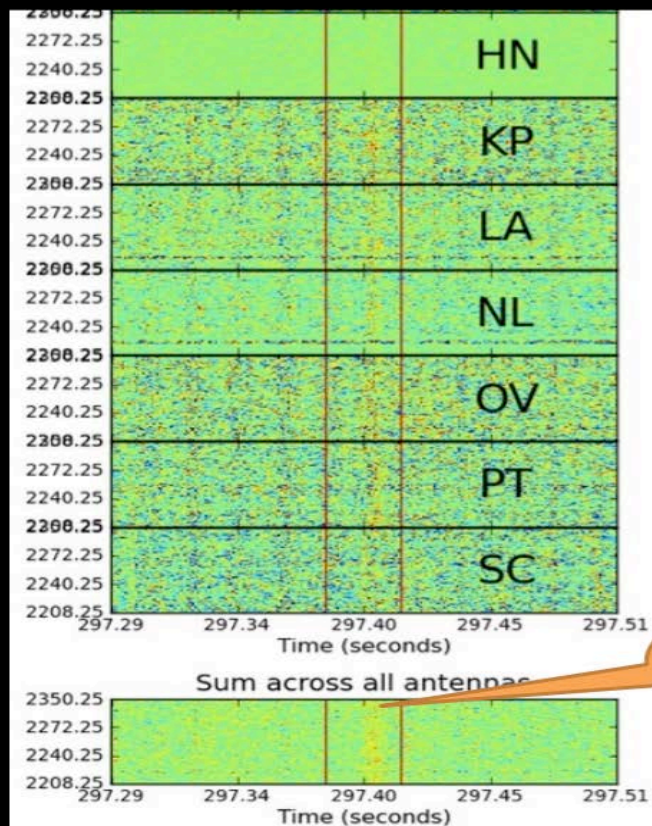


Constraint based scheduling for NASA's Deep Space Network
Demand forecasting [SpaceOps 2018], Midrange scheduling [AIMAG 2014], near real-time scheduling
Link complexity based scheduling [SpaceOps 2018]

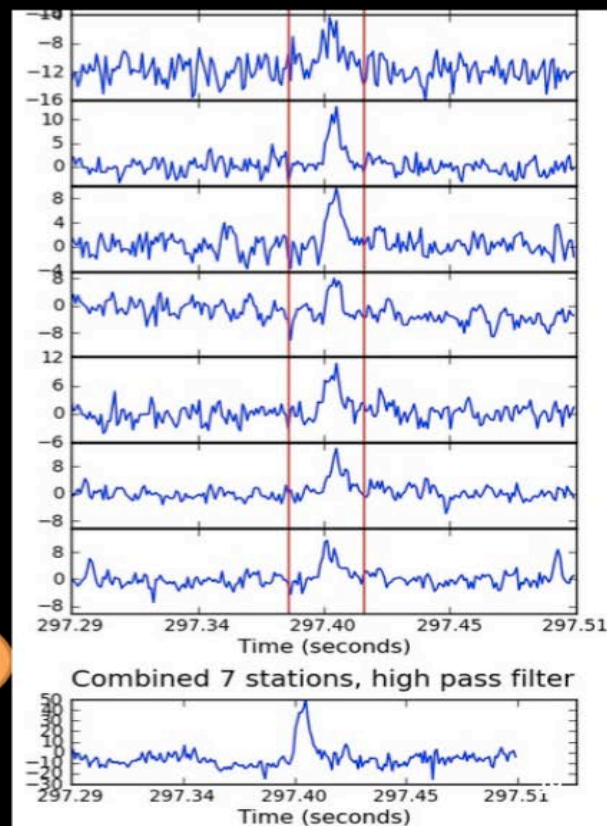


Machine Learning for Automated Triage/detection of Visual Transient Events
Intermediate Palomar Transient Factory (i-PTF)
Continuous quality control and retraining
 $10^3 \rightarrow 50$

Rebbapragada et al.



Pulsar!



Machine Learning for Automated Triage/classification of Radio Transient Events
 Very Long Baseline Array (VLBA) Fast Transients Experiment (V-FASTR)
 $10^5 \rightarrow 50$ per 24h
 Random Decision Forests, continuous quality control and retraining.

Wagstaff et al. 2016

Mars Target Encyclopedia

- Lunar and Planetary Science Conference

- Three years
- 5,920 documents
- 2-page abstracts
- 7.2M words



Entities

Find
Elements,
Minerals,
Targets

Relations

Classify pairs
of Target +
(Element or Mineral)

MTE
Database

Wagstaff et al. 2018 IAAI

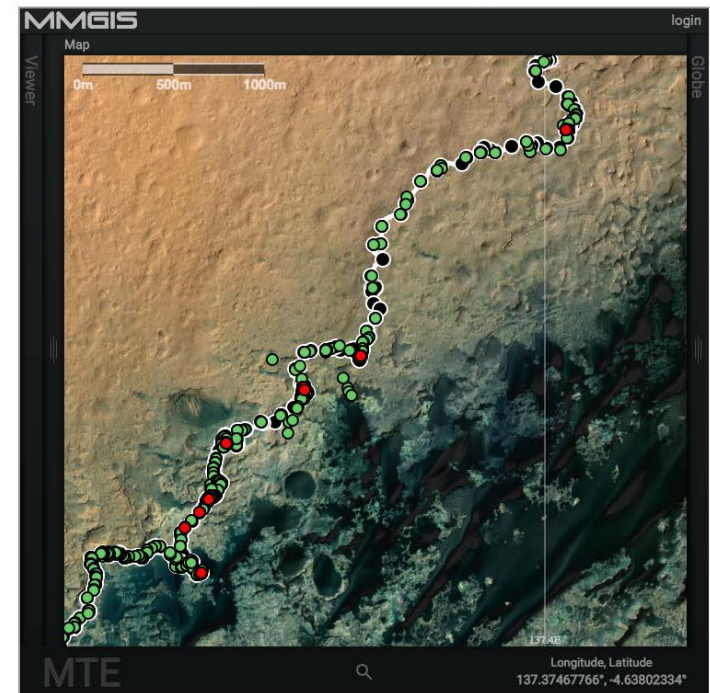
Mars Target Encyclopedia

Compositional information from publications about MSL ChemCam surface targets
Publications currently indexed: abstracts from LPSC 2015 and 2016

hematite

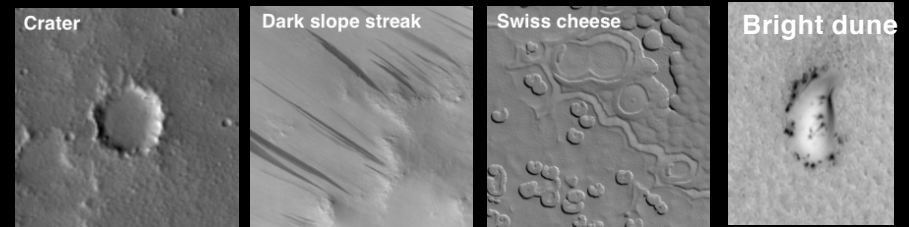
9 targets found

 Confidence_Hills 46 properties 8 publications	 Windjana 103 properties 10 publications	 Augusta 1 property 1 publication
 Big_Sky 9 properties 2 publications	 Buckskin 11 properties 3 publications	 Engo 1 property 1 publication
 Maturango 8 properties 2 publications	 Stovepipe_Wells 3 properties 1 publication	 Tsumeb 1 property 1 publication



Deep Mars CNN Classification of Mars Imagery for the PDS Imaging Atlas

- MSL Rover data set¹
 - 6,691 labeled images (Mastcam L/R eye, MAHLI)
 - 24 classes
- MRO HiRISE data set²
 - 10,433 labeled images
 - 8 classes
 - Augmentation: rotation, flipping, brightness adjustment

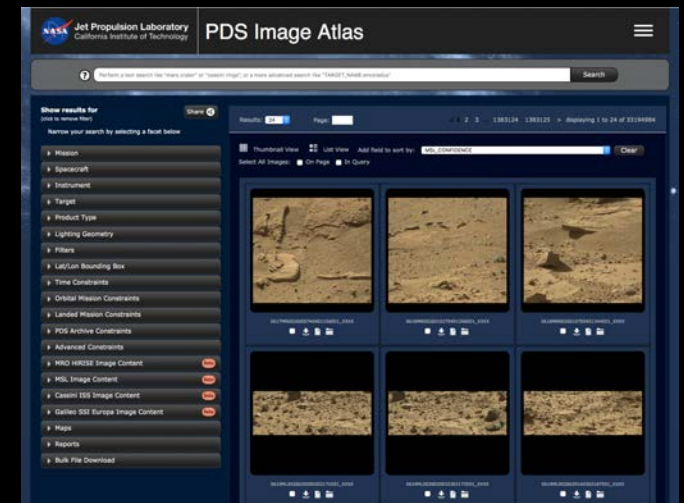


Example images for HiRISENet

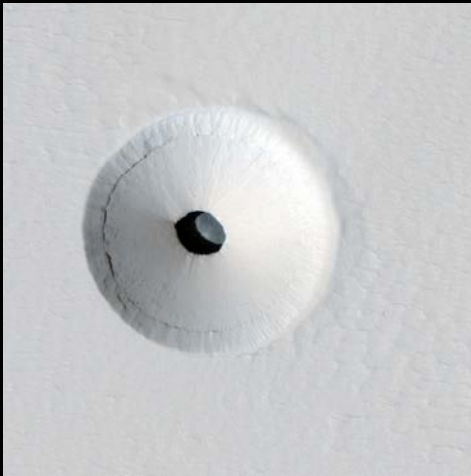


Example images for MSLNet

Result: Content indexing for
PDS Atlas

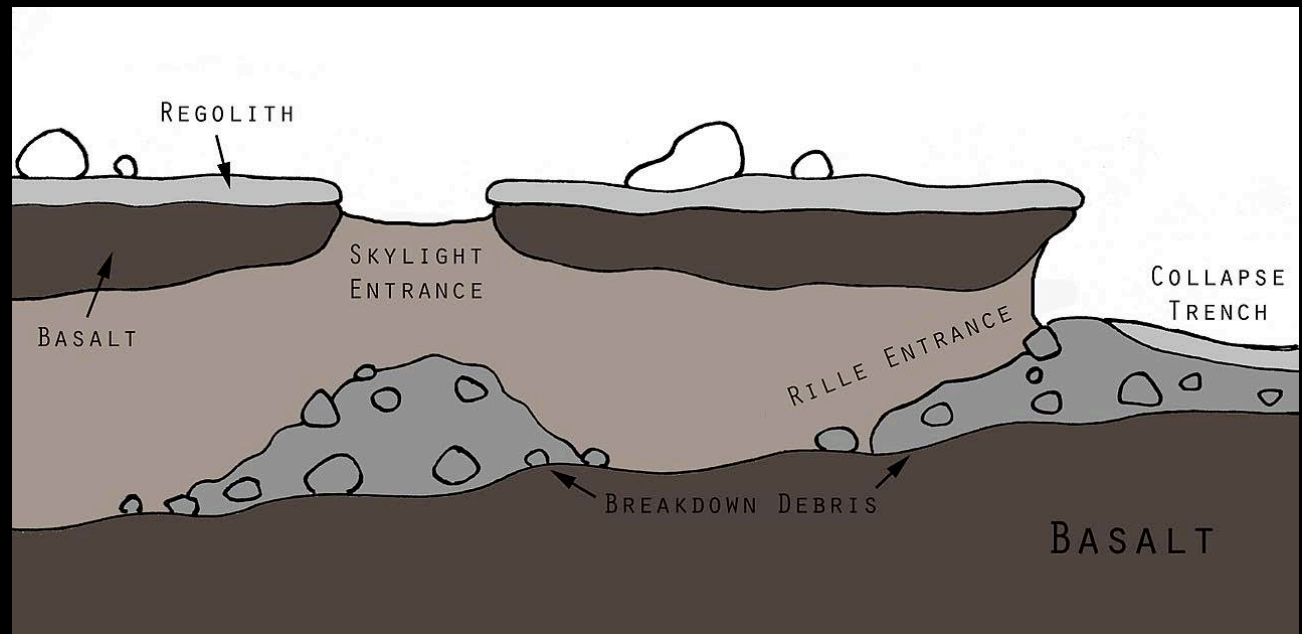


Cave Exploration



Artists concept.

Predecisional, for
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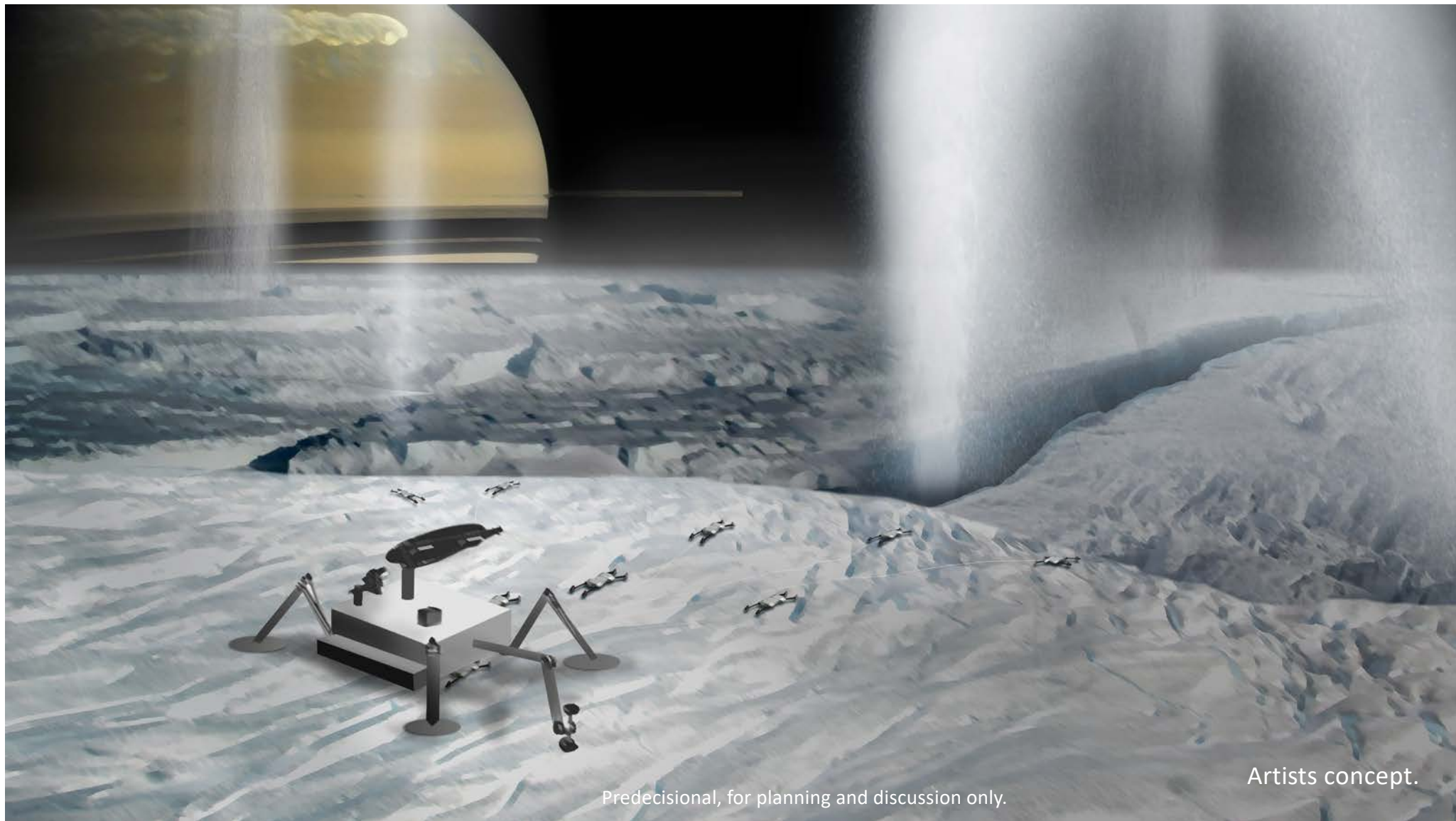
Rovers exploring Cave may depend on batteries for power → mission duration of days

- With such a short mission, rovers cannot wait for instructions from Earth
- True “Fire and forget” mission, completely autonomous

Dynamic Zonal Allocation Algorithm

- Each rover maps a pre-assigned zone of the cave
- Rovers deep into the cave must expend more energy driving
- Rovers closer to the cave entrance expend more energy relaying data from deeper rovers to the cave entrance
- Algorithm robust to loss of rovers – adjacent rovers shift to cover newly uncovered area
- Algorithm extends to “sneakernet” driving to cover areas beyond communications range

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Visualization.



Predecisional, for planning and discussion only.

Artists concept.

NEO 100 Concept

Economically Assay 100 Near Earth Objects



Predecisional, for planning and discussion only.

Artists concept.

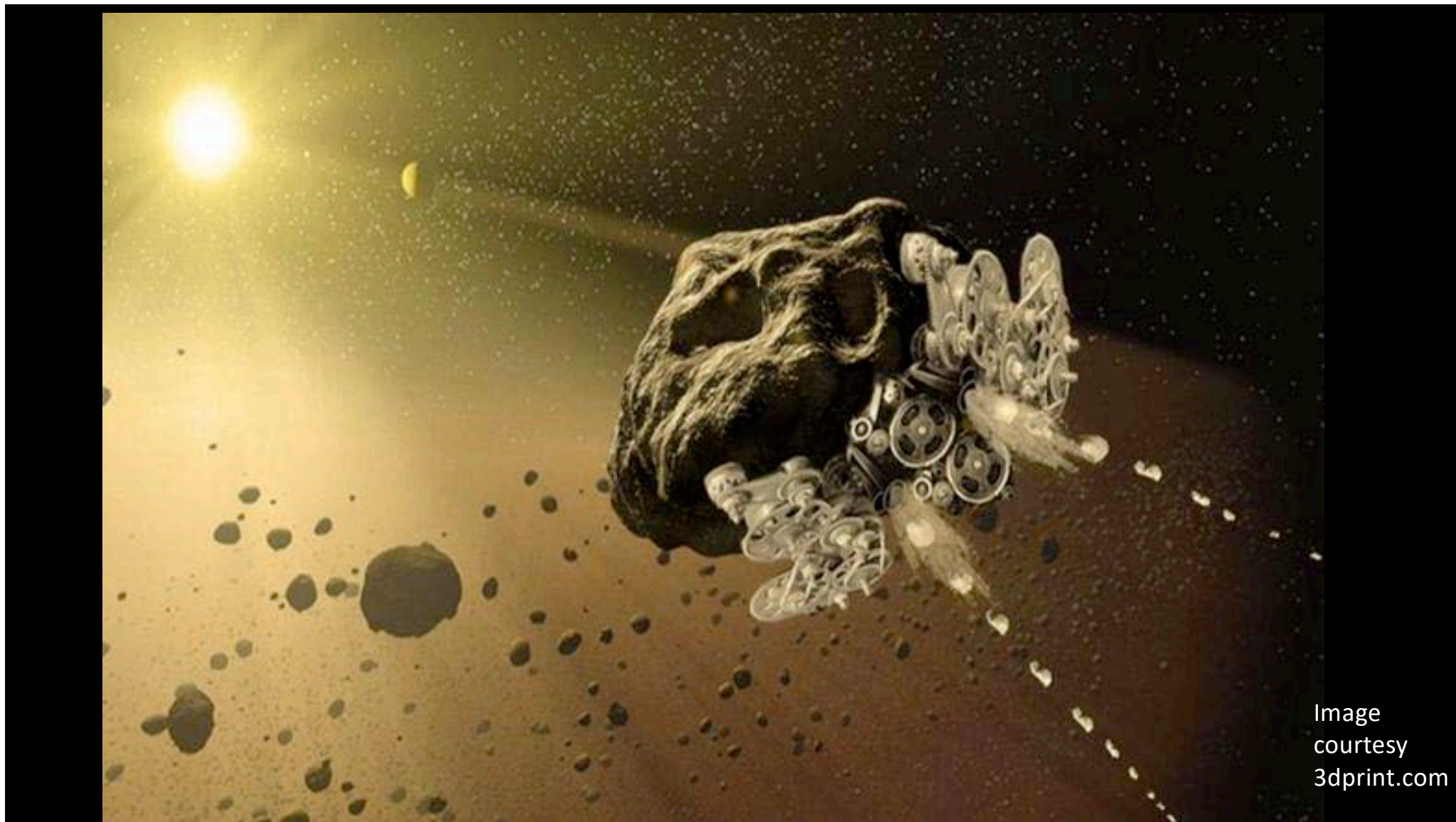


Image
courtesy
3dprint.com

Lewis and Clark 1804-1806

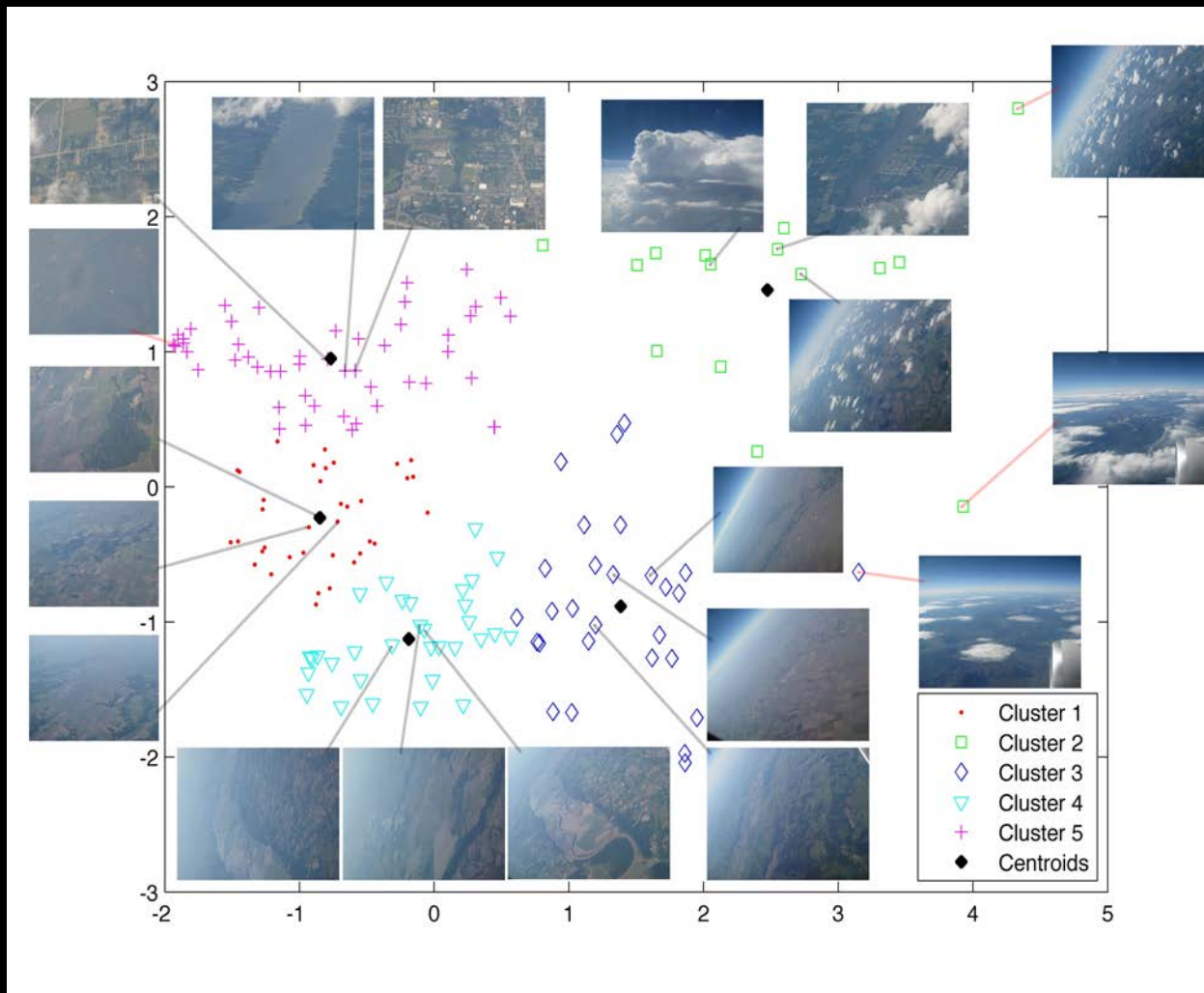
mountains

rivers

lake

wildlife

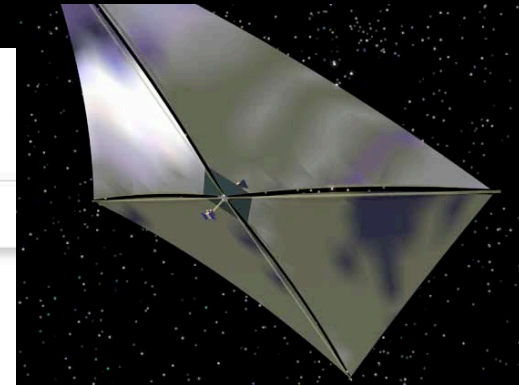




Clustering and Metric Learning of Aerial Imagery [Hayden et al. 2012 ACM TIST]

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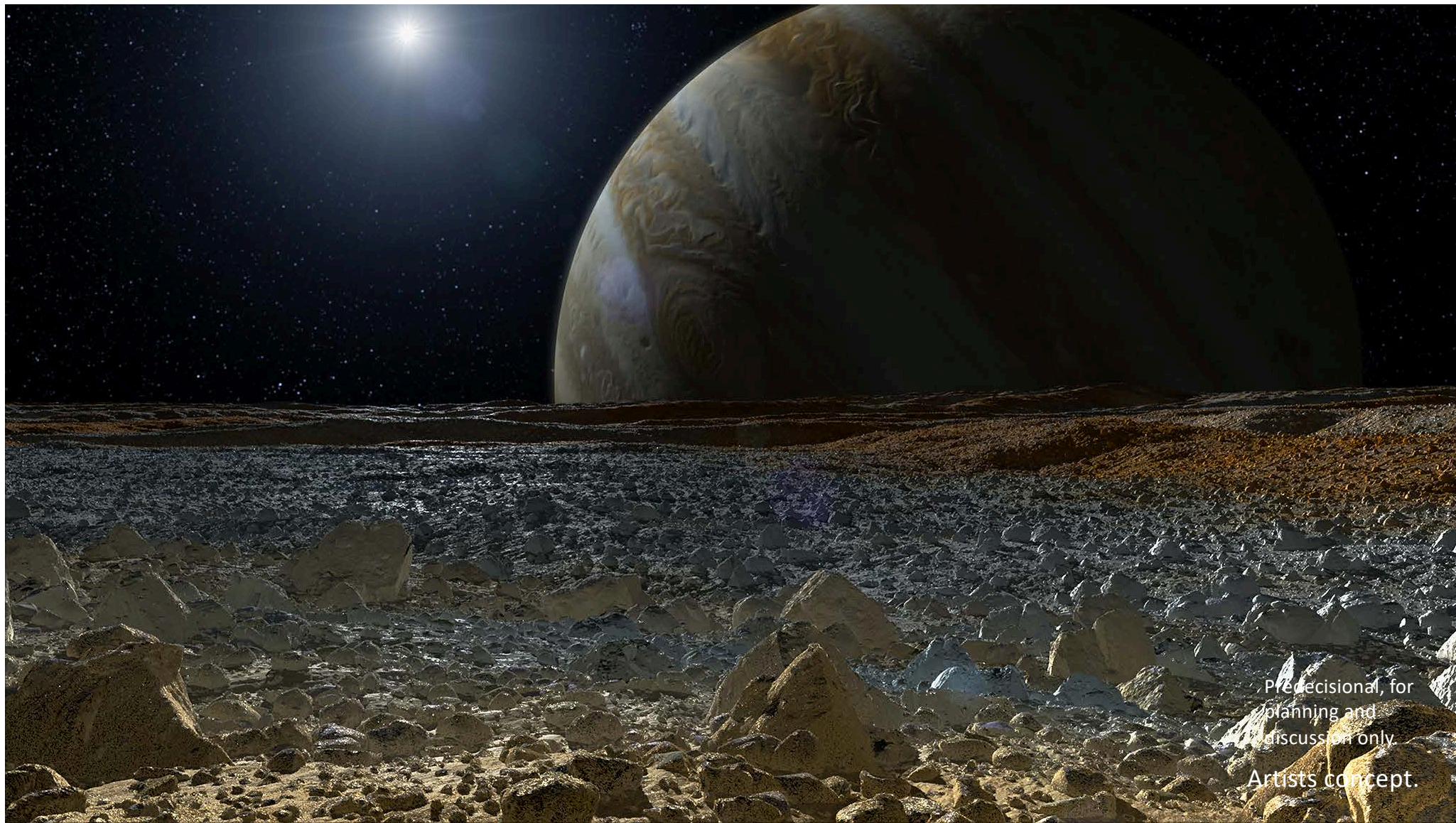
LATEST

ENGINEERING

How NASA's Search for ET Relies on Advanced AI

Jet Propulsion Laboratory's artificial intelligence chief describes the "ultimate" test for AI in space exploration

By Larry Greenemeier on December 28, 2017

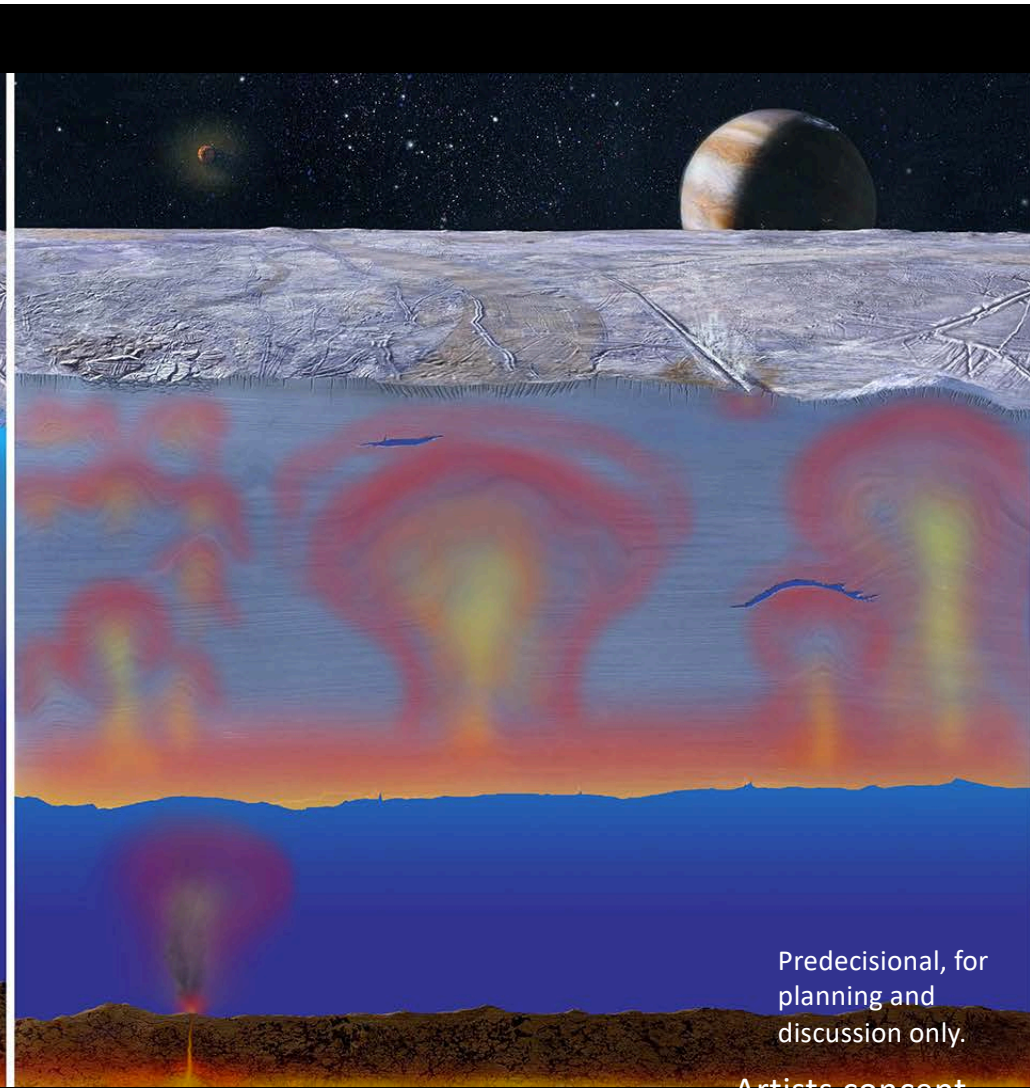
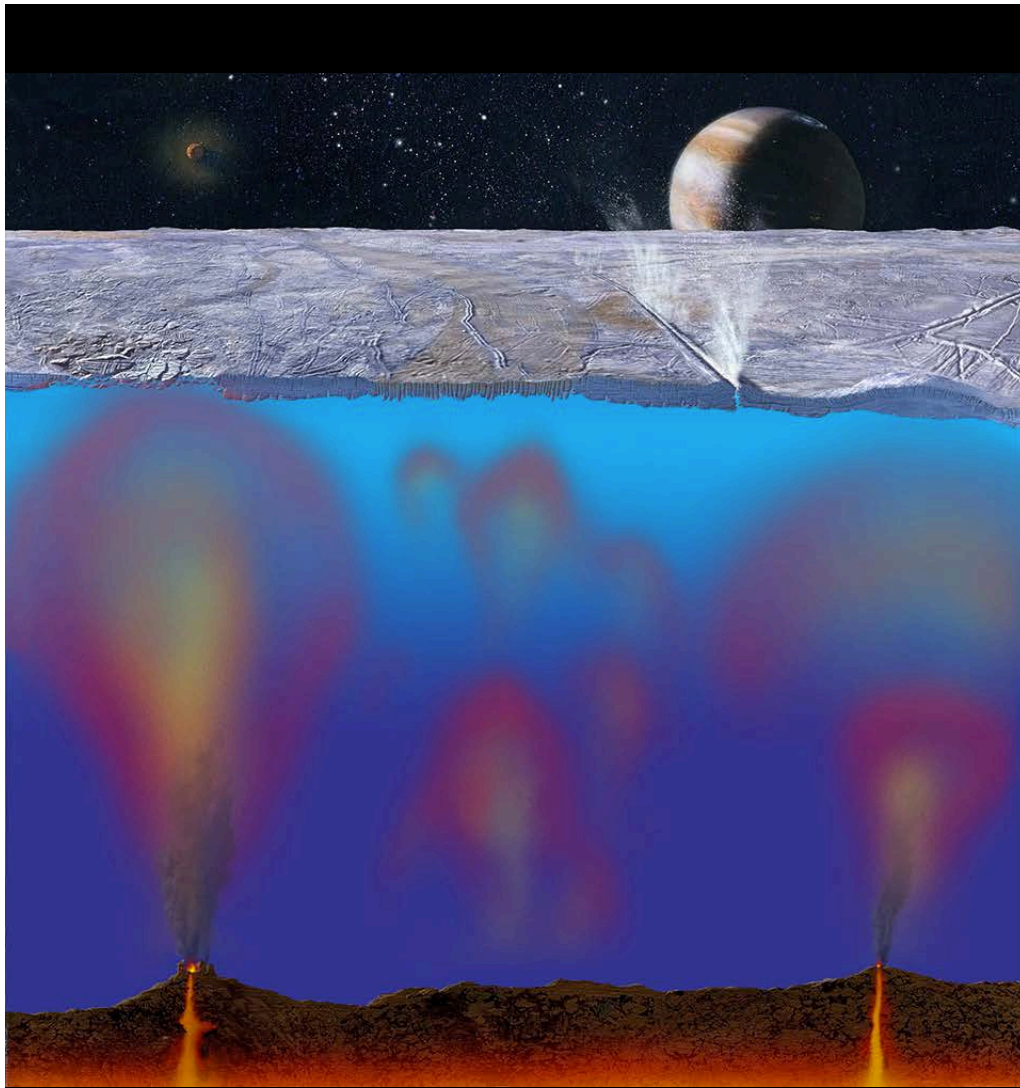


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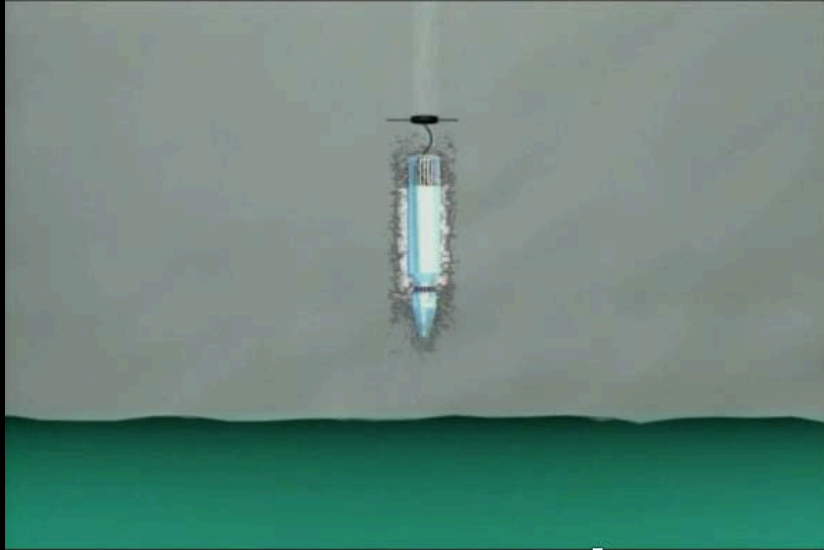


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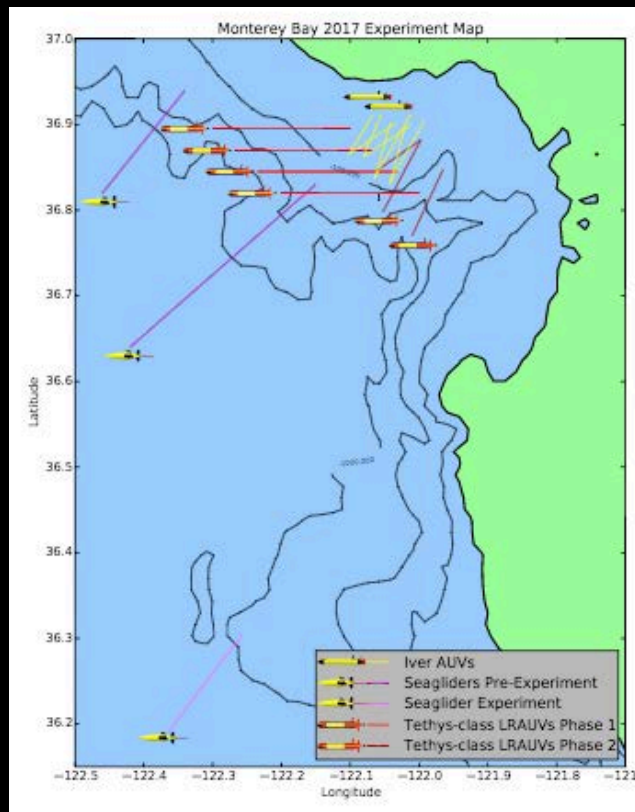


- A Europa Submersible would have spend a year or even more to penetrate kilometers of ice
- Then explore autonomously for weeks to months at a time searching for life, perhaps at hydrothermal vents
- A true challenge for AI!

Predecisional, for
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discussion only.

Ocean
Worlds
submersible
concept.

Deployment May 2017 (KISS)



POC: A. Thompson / Caltech
S. Chien, A. Branch / JPL



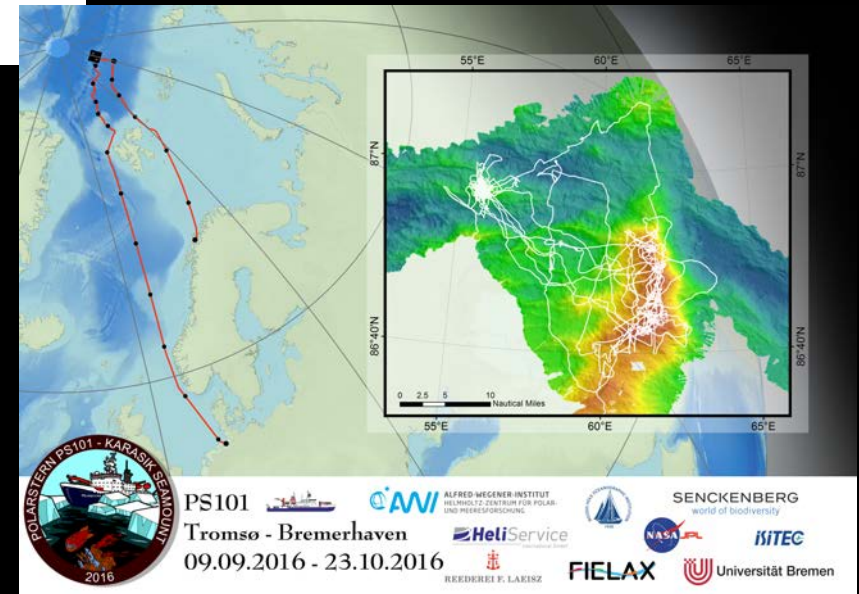
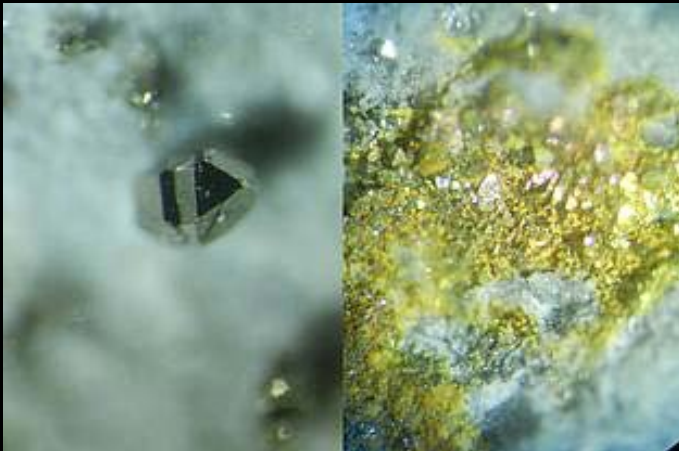
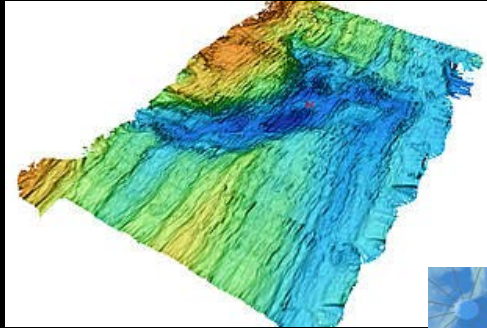
Figure 7: Kongsberg Underwater Technology, Inc. Seaglider onboard the R/V *Paragon*



Figure 6: OceanServer Technology, Inc. Iver2 AUVs onboard the R/V *Shana Rae*

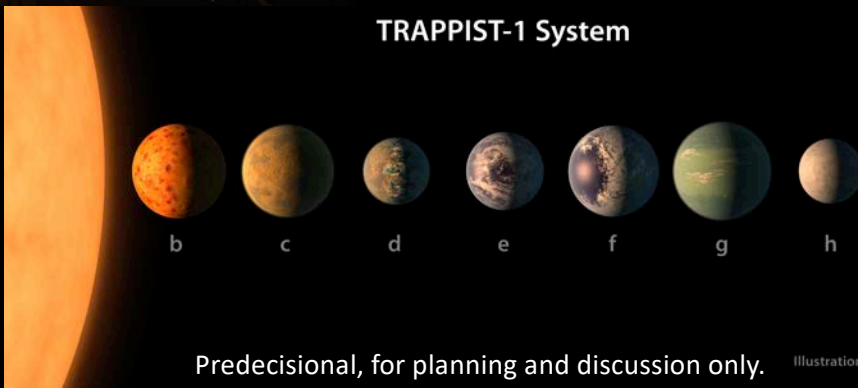
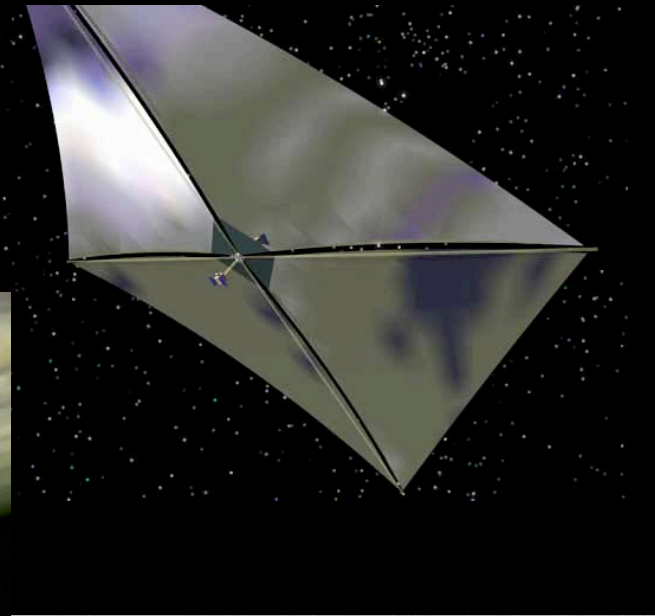
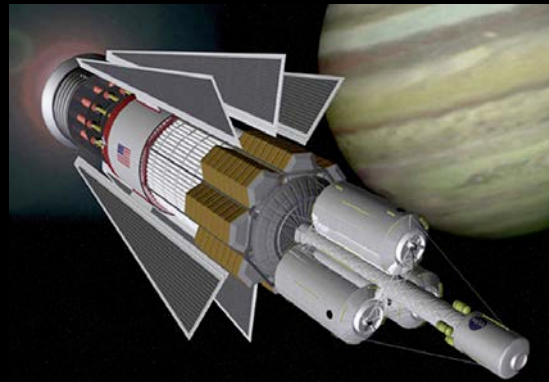


From the Recent Polarstern Cruise, Karasik Massif 85 N



Images courtesy of A. Boetjius/AWI, C. German/WHOI, K. Hand/JPL

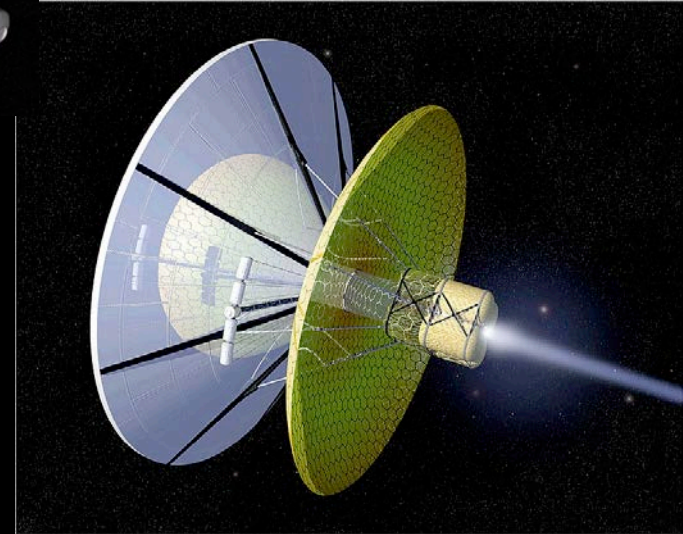
Interstellar Mission Concepts



TRAPPIST-1 System

Artists concepts.

Predecisional, for planning and discussion only. Illustration



For further information on Autonomous Sciencecraft Onboard Instrument Processing see:

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Davies, A. G., S. Chien, V. Baker, T. Doggett, J. Dohm, R. Greeley, F. Ip, R. Castano, B. Cichy, R. Lee, G. Rabideau, D. Tran and R. Sherwood (2006) Monitoring Active Volcanism with the Autonomous Sciencecraft Experiment (ASE). *Remote Sensing of Environment*, Vol. 101, Issue 4, pp. 427-446.
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- Sulfur:
L. Mandrake, U. Rebbapragada, K. Wagstaff, D. Thompson, S. Chien, D. Tran, R. Pappalardo, D. Gleeson, R. Castano, "Surface Sulfur Detection via Remote Sensing and Onboard Classification," *ACM Transactions on Intelligent Systems Technology*, Special Issue on AI in Space, Vol. 3 No. 4, 2012.
D. F. Gleeson, R. Pappalardo, S. Grasby, M. Anderson, B. Beauchamp, R. Castano, S. Chien, T. Doggett, L. Mandrake, K. Wagstaff, "Characterization of a sulfur-rich Arctic spring site and field analog to Europa using hyperspectral data," *Remote Sensing of Environment* (2010), doi:10.1016/j.rse.2010.01.011
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- **ASE Architecture, Overview:**

S. Chien, R. Sherwood, D. Tran, B. Cichy, G. Rabideau, R. Castano, A. Davies, D. Mandl, S. Frye, B. Trout, S. Shulman, D. Boyer, "Using Autonomy Flight Software to Improve Science Return on Earth Observing One, Journal of Aerospace Computing, Information, & Communication, April 2005, AIAA.

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- **Operations of EO-1 before and after ASE:**

G. Rabideau, S. Chien, R. Sherwood, D. Tran, B. Cichy, D. Mandl, S. Frye, S. Shulman, R. Bote, J. Szwachkowski, D. Boyer, J. Van Gaasbeck, Mission Operations with Autonomy: A preliminary report for Earth Observing-1, International Workshop on Planning and Scheduling for Space, Darmstadt, Germany, June 2004.

- **Validating the Autonomous Sciencecraft:**

B. Cichy, S. Chien, S. R. Schaffer, D. Tran, G. Rabideau, R. Sherwood, D. Mandl, R. Bote, S. Frye, B. Trout, S. Shulman, J. Hengemihle, J. D'Agostino, J. Van Gaasbeck, D. Boyer, "Validating the Autonomous EO-1 Science Agent," International Workshop on Planning and Scheduling for Space, Darmstadt, Germany, June 2004.

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